GPFA-AB Reservoirs Methodology Memo

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The Natural Reservoirs Task of the Appalachian Basin Geothermal Play Fairway Analysis project involves mapping and characterizing the proven natural reservoirs, which have the potential to be utilized for geothermal energy production within the Appalachian Basin region of New York (NY), Pennsylvania (PA), and West Virginia (WV). The results of this task are intended to accompany the analyses of the Thermal Resource, Seismic Risk, and Utilization tasks, for the purpose of a Combined Risk Map (CRM) to determine the most optimal locations in the basin for future geothermal investment. The goals of the Natural Reservoirs task were:

i. Collect data on known natural reservoirs in the Appalachian Basin, and integrate data sources for consistency,
ii. Research geologic formations in the basin to populate empty fields in the database,
iii. Choose or develop a metric for quantifying reservoir favorability,
iv. Predict the likely range of outcomes for all natural reservoirs in the basin, and
v. Map the reservoir results in a Geographic Information System (GIS)

Reservoir data collection and compilation methods differed state by state; however, reservoir analysis and uncertainty quantification methods are consistent across the tristate region. This memo and its accompanying appendix presents a detailed description of all methods that were used for the completion of this task's milestones.

1. The Desired Resource: Natural Reservoirs

For the purposes of this project, a geothermal reservoir is defined as a volume of rock in the subsurface that has sufficient permeability to allow fluids to flow through it. Fluids are pumped into one well, heated by contact with the rock, and pumped back to the Earth's surface via a second well. This scope of this project was limited to consideration of naturally-occurring reservoirs, or those in which sufficient permeability already exists. Enhanced or Engineered Geothermal Systems (EGS)—the process by which permeability is artificially created in a rock using high pressure fluids—was excluded from the analysis as described in the Statement of Project Objectives (SOPO).

Because this project was limited to the analysis of existing data, our proposal hinges on the application of subsurface data that has already been collected by the petroleum industry via drilling for oil and gas. Such non-proprietary datasets of proven conventional hydrocarbon reservoirs generally include depth, thickness, location, spatial extent, porosity, and less frequently permeability, though publicly available data vary from state to state and from basin to basin. Analyzing petroleum reservoirs for geothermal exploration may lower geothermal project risk because:

i. Non-proprietary hydrocarbon reservoir data is already collected and access to those data is low- or no-cost
ii. Hydrocarbon reservoirs have some degree of inherent porosity and permeability given that large amounts of hydrocarbons existed within and flowed out of those reservoirs.
iii. Sedimentary units generally have higher permeability values than crystalline igneous or metamorphic units, in which hydrothermal or EGS projects generally occur.

2. Data Collection

The reservoir dataset available for New York differed from that of Pennsylvania and West Virginia. This section describes the differences between the two datasets.

2.1. Pennsylvania and West Virginia

Extensive data collection and reservoir mapping was completed in the early 2000s for the purpose of carbon sequestration research through the Midwest Regional Carbon Sequestration Partnership (MRCSP). A GIS database from the MRCSP was available for use as a starting point for this project, courtesy of the West Virginia Geological and Economic Survey (WVGES). The dataset is not open-source, but it can be purchased from the WVGES. The dataset includes oil and gas reservoirs located in PA and WV, but does not include reservoirs in NY. The MRCSP calculated potential storage volume for the reservoirs by using a volumetric analysis (total volume of rock corrected by reservoir porosity); therefore, the following reservoir parameters were included in the dataset: average reservoir production depth, reservoir name, formation code (geologic code for the producing formation, see Appendix), state, reservoir pressure, porosity, net thickness, and shapefiles (polygons).

Due to the large size of the PA and WV database and narrow time constraints of the Phase One GPFA, reservoirs shallower than our chosen threshold were trimmed from the database to reduce the workload. To pick the depth threshold, a temperature threshold of 40ºC was first selected using the Lindal Diagram of temperatures and potential end-uses (Lindal, 1973). An average geothermal gradient and surface temperature for the region (calculated from the Thermal Resource Task) resulted in a threshold of 1250 meters (4100 feet).

2.2. New York

The dataset from carbon sequestration research conducted in NY was available to us through the New York State Geological Survey (NYSGS); however, it did not prove useful to our project because it does not contain any information about potential reservoirs except for their depth. Because New York joined the MRCSP years later than the other states in the Consortium, their efforts did not produce the same final data products or use the same volumetric analysis method as for WV and PA. NYSGS instead approximated the storage potential for carbon dioxide sequestration using oil and gas production volumes to estimate storage capacity of each reservoir. Because porosity and thickness values were not required to conduct their analyses those parameters are not included in the database.

Instead, we used the Empire State Organized Geologic Information System (ESOGIS) online database to access the information that was required for this project. This dataset holds data by well rather than by reservoir. Well locations (latitude and longitude) were downloaded from ESOGIS and uploaded into a GIS. To create reservoir area polygons similar to those in the database for PA and WV, we used a GIS tool to create "buffer zones" around wells that pertain to a given reservoir. For details on the process of calculating the reservoir well buffer, see the accompanying Appendix.

The available digital well data from ESOGIS included well Total Vertical Depth (TVD), producing formation, reservoir name, latitude, and longitude. Reservoir thickness was not available in the digital database, and was extracted manually from downloaded PDFs of Well Completion Reports.

The ESOGIS database does not report either formation or reservoir porosity as a separate data field. Porosity data for each reservoir in NY had to be extracted from the published literature. In the interest of time, the reservoirs were categorized by producing formation, and

an average reservoir porosity was assigned to each formation based on values reported in literature. Details on porosity value choices can be found in the Appendix.

No minimum temperature threshold for reservoir analysis was necessary for NY, as the database was small enough to be evaluated by the available personnel in a short time. This decision was made knowing that any shallow reservoirs in NY would be eliminated once the thermal map was integrated with the reservoir map.

2.3. Permeability

Neither the MRCSP database nor ESOGIS contains information about reservoir permeability, which is the most important parameter for estimating reservoir favorability. Reservoirs across the basin were again grouped by producing formation, and a permeability value was assigned to each reservoir based on published values for its formation, or an empirical relationship with porosity. For more details on the process of estimating permeability for each formation, see Appendix.

3. Reservoir Favorability Metrics

Following the compilation of the three-state reservoir database, reservoir favorability metrics were chosen using the available parameter constraints: permeability, thickness (hydrocarbon pay thickness), temperature, depth, and area. Three metrics were ultimately chosen to express reservoir favorability: one is a geologic quality metric that serves mostly as a reservoir ranking tool and relies only on the geologic properties detailed above; the other two include engineering inputs to predict production-stage performance of the reservoirs. The Reservoir Flow Capacity (RFC) is the metric that is used as a comparator for the geologic parameters in each reservoir. The latter metrics are the Reservoir Productivity Index for supercritical CO_2 (RPI_g) and for water

(RPI_w), used to quantify potential productivity, or fluid flow rate, in each reservoir during production. The following sections describe each metric and their purposes.

3.1. Reservoir Flow Capacity

The reservoir flow capacity (RFC) was chosen as a favorability metric not only because it is comprised of only geologic parameters, but also because the levelized cost of energy is sensitive to this metric (Sanyal and Butler, 2009). This metric provides the opportunity to compare the quantitative favorability of each reservoir relative to the other reservoirs based on its natural reservoir qualities only. The RFC, shown as F below in units of mD-m, is a simple equation comprised of only permeability k in millidarcies (mD), and thickness H in meters:

$$F = kH \tag{1}$$

3.2. Reservoir Productivity Index

A separate metric was chosen for this project as a means of quantifying the favorability of the reservoirs in the basin during energy production. After thermal quality, flow rate is the second-most important factor affecting geothermal heat production (Bedre and Anderson, 2012). The petroleum industry often uses a term called the well productivity index (PI) to quantify the flow of a given oil or gas well producing from a hydrocarbon reservoir. The PI is defined as the volumetric flow rate of a well divided by the pressure drop from the reservoir to the producing well:

$$PI = \frac{Q}{\Delta P} = \frac{2\pi kH}{\mu ln\frac{D}{r_w}} \tag{2}$$

where Q is flow rate (m^3/s), ΔP is the pressure drop from the reservoir to the production well (Pa), k is permeability (m^2), H is reservoir thickness (m), μ is the fluid viscosity (Pa-s), D is the distance between the injection and production well (m), and r_w is the wellbore radius (m)

(Gringarten, 1978). Equation 2 assumes that the reservoir is a homogeneous porous medium with horizontal intergranular flow.

PI has also been used to characterize the productivity of a well doublet for geothermal reservoirs, for both EGS reservoirs and sedimentary aquifer reservoirs (Gérard et al., 2006; Sanyal and Butler, 2009; Augustine, 2014; Cho et al., 2015; Hamm et al., 2016). The PI metric was adapted to this project by using it as an approximation of a reservoir's productivity, rather than just a well pair. The metric is identical to Equation 2, but is called the Reservoir Productivity Index (RPI) and the parameters used are average reservoir values. Additionally, mass flow rate (kg/s) was used instead of volumetric flow rate, so that RPI can be compared fairly for an incompressible liquid and a compressible gas as the working fluid. RPI is used as the model in a Monte Carlo Simulation to predict the uncertainty associated with each reservoir, which is described below.

The RPI was subdivided by the type of working fluid that could be used in the geothermal system. Water (RPI_w) and supercritical carbon dioxide (sCO_2; RPI_g) were chosen as the two working fluid options for this project. For each reservoir, RPI_w and RPI_g were modeled. The differences between RPI_w and RPI_g are the respective inputs for viscosity and permeability.

3.2.1. Viscosity

The viscosity of water varies with temperature, therefore the temperature at the depth of each reservoir was calculated. Because the thermal and reservoir tasks were being completed simultaneously, reservoir-specific temperatures at depth were not available. Therefore, state-wide averaged thermal gradients and surface temperatures were used for this work. Uncertainty can be reduced in future work by applying reservoir-specific

estimates of temperature at depth for a more accurate estimate of fluid viscosity. The following values in Table 1 are averages taken from work done by Smith (2015). Those geothermal gradients and surface temperatures were used to calculate the temperature at the depth of each reservoir using the following equation modified from Tester et al. (2012):

$$T(z) = z_r \frac{dT}{dz} + T_s \quad (3)$$

where z_r is the depth of the reservoir in meters, $\frac{dT}{dz}$ is the temperature gradient in ºC/km, and T_s is the temperature at the surface in ºC (Table 1). The dynamic viscosity of water as it varies with temperature (Engineering Toolbox, 2015) is presented in

Table *2*. The effects of salinity on viscosity were assumed to be negligible.

Table 1. Average temperature gradient and surface temperatures for New York, Pennsylvania, and West Virginia. Values averaged from work done by Smith (2015).

	Gradient (ºC/km)	Average Surface Temperature (ºC)
New York	22.19	9.66
Pennsylvania	21.19	11.33
West Virginia	23.19	13.87

Table 2. Dynamic viscosity of water as a function of temperature. Temperatures are categorized in 10º increments (Engineering Toolbox, 2015).

Temperature (ºC)	Viscosity, water (Pa-s)
< 30	0.000900
30-39.99	0.000726

40-49.99	0.000600
50-59.99	0.000507
60-69.99	0.000436
70-79.99	0.000380
80-89.99	0.000335
90+	0.000299

Data for dynamic viscosity of sCO_2 come from Ouyang (2011). The viscosity of sCO_2 varies as a function of both temperature and pressure. The assumed pressure of the injected sCO_2 was 10 MPa (100 bar; 1500 psi). At all temperature ranges at a pressure of 10 MPa, the estimated viscosity of sCO_2 is 0.00002 Pa-s.

3.2.2. Permeability

Most permeability values are derived from direct measurement of cored rock samples using a gas as the fluid. Use of the raw permeability measurements (k_g) is acceptable when estimating the flow of a gas through a reservoir rock, but not when trying to estimate the flow of water through the rock, which is the typical fluid used in geothermal systems. In the case of RPI_g, the gas permeability was retained because the viscosity of sCO_2 is much like that of a gas (Brown, 2000; Pruess, 2007); however, for RPI_w the gas permeability was corrected for the Klinkenberg effect. This correction is more important

for low permeability rocks than high permeability rocks (Tanikawa and Shimamoto, 2006). Since most reservoirs in the Appalachian Basin are of low permeability, this is an important step for the RPI_w calculations.

Corrections were applied to all reservoirs based on the reservoir's primary lithology. For carbonate reservoirs, the following correlation from Al-Jabri et al. (2015) was applied,

$$k_w = 0.578 {k_g}^{1.097} \quad (4)$$

where k_w is the permeability of the rock with water, and k_g is the permeability of the rock with gas, both in units of mD. For all other lithologies, the following correlation from Jones (1987) was used:

$$k_w = \frac{k_g}{1+\frac{b}{p}}; \quad (5)$$

$$b = 15.61 \left(\frac{k_g}{\phi}\right)^{-0.447} \quad (6)$$

where p is the mean flowing pressure in psi, and ϕ is the porosity as a decimal fraction.

3.2.3. Thickness

The MRCSP dataset holds values for each reservoir's net pay thickness, or the vertical column from where oil and gas was produced. The New York ESOGIS database does not contain information on reservoir thickness, so pay thickness was extracted manually from well production reports downloaded from ESOGIS. If the producing interval was not reported, then the perforated interval was used as an approximation. The pay thicknesses from all wells in each reservoir were averaged to calculate the mean reservoir pay thickness.

3.2.4. Well Distance and Wellbore Radius

These geothermal field design parameters were held as constants in the RPIw and RPIg equations. D, or distance between wells, was assumed to be 1000 m, while r, or wellbore radius, assumed to be 0.1 m. These parameters were not used in the RFC equation.

3.3. Reservoir Architecture and Flow Considerations

During the database compilation phase of this project, our reservoirs were categorized as either stratigraphically-controlled (porous medium) or structurally-controlled (fractured medium), based on what is known about the reservoirs from literature (i.e. Roen and Walker, 1996). The original intention was to calculate the RFC and RPI of each reservoir using an appropriate equation based on the flow type; however, in the allotted time of the project, a comparable equation for fracture-dominated reservoirs was not identified. Therefore, the equation for RPI in porous medium reservoirs was applied to all reservoirs as a first-order approximation, regardless of reservoir architecture.

4. Uncertainty

An important piece of this project is the quantification of uncertainty in reservoir data, and therefore, also in the uncertainty of the calculated RFC, RPI_g and RPI_w for each reservoir in the basin. In order to calculate the range of possible outcomes (RFC, RPI_g and RPI_w) for each reservoir, we performed a Monte Carlo Simulation on each metric. To do this, the required inputs for each variable were the average value, the standard deviation, and probability distribution type (normal, log-normal, etc.).

4.1. Reservoir Parametric Uncertainty Index

Each average parameter value (i.e. k, H, μ) from the database has inherent uncertainty associated with it, both in terms of the variation in data quality and in terms of the natural

variation, or heterogeneity, of each reservoir. Though average parameter values were available in the database for each reservoir, standard deviations and probability distributions were not, and therefore had to be selected. To maintain consistency during the assignment of standard deviations and distribution types to each parameter for all the reservoirs, we created an uncertainty index that ranges from 0 (no uncertainty) to 5 (most uncertain).

Each uncertainty index value (0-5) corresponds to the likely standard deviation from the parameter input, shown in Table 3. The standard deviation increments for each parameter were chosen based on reports in reservoir literature of typical variations in reservoir thickness, permeability, and temperature (which affects the fluid viscosity) due to heterogeneity (i.e., Murtha, 1994; Society of Petroleum Engineers, 2001; Satter et al., 2008; Peters, 2012).

Because the sources of data for the average parameter value were not equally reliable for all reservoirs, data quality guided the selection of the uncertainty index value for each reservoir's parameters, as shown in the example in Table 4. For example, permeability data that was calculated from a published empirical porosity-permeability relationship for the respective geologic formation and region would be assigned an uncertainty factor of 2. That reservoir's average permeability value would therefore be assigned a standard deviation of 25% with a log-normal distribution. Additionally, each parameter was assigned a probability distribution type for a Monte Carlo Simulation. Distribution types were determined based on reservoir engineering and modeling best practices and literature. More details on how the uncertainty indices were assigned can be found in the Appendix.

Table 3. Uncertainty Index reference chart for each parameter in the Monte Carlo Simulation model.

Uncertainty Index	**Permeability**	**Thickness**	**Viscosity**
	k	H	μ
0	0%	0%	0%
1	12.5%	10%	10%
2	25%	20%	20%
3	50%	30%	30%
4	100%	40%	40%
5	200%	50%	50%
Probability Distribution	log-normal	triangular	normal
References	Murtha, 1994; Satter, 2008	Peters, 2012; SPE, 2001	Based on temperature distribution from Smith (2015)

Table 4. Example of Uncertainty Index assignment criteria for reservoir permeability data.

1	• Data from a published empirical porosity-permeability relationship, applicable to the respective geologic formation and reservoir.
2	• Data from a published empirical porosity-permeability relationship, applicable to the respective region and formation but not the respective reservoir.
3	• Data from unpublished empirical porosity-permeability relationship, applicable to the respective geologic formation but not the respective reservoir. • Data are a published or unpublished range of values or average value for the respective geologic formation and region.
4	• Data come from unpublished empirical porosity-permeability relationship • An average value can be applied from a similar formation or the same formation located in another region • Data are a published or unpublished range of values or average value for a similar geologic formation in the respective region
5	• Generic low value (≤1mD) assigned due to lack of available data

4.2. Monte Carlo Simulation

A Monte Carlo Simulation with 100,000 repetitions was coded in MatLab and performed on the RFC, RPI_g, and RPI_w for each reservoir, with inputs for parametric mean, standard deviation, and distribution. The simulation generated stochastic results for each reservoir,

using the assigned uncertainty indices and parameter probability distributions in Tables 3 and 4. From those data outputs, the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile results were calculated. The 50^{th} percentile is the median, or the most likely, result.

4.3. Uncertainty Metric

The metric deemed most useful for illustrating the uncertainty of each reservoir was the Coefficient of Variation (CV), which is the ratio of the standard deviation of the sample to the mean of the sample (Jensen et al., 2000). Using the CV allowed us to normalize the result (RFC, RPI_g, and RPI_w) of each reservoir by its uncertainty. For example, a reservoir with a low CV has a smaller standard deviation relative to its mean, and therefore there is less uncertainty about its predicted RFC, RPI_g or RPI_w.

5. Quality Thresholds for Mapping

Thresholds for the reservoir favorability metrics are required to segregate the reservoirs into favorability 'grades' for mapping. A five-grade threshold map was required by the project SOPO. Threshold choices based on conversations with experts and the results of the Monte Carlo Simulation are listed below.

5.1. Reservoir Flow Capacity Thresholds

Because RFC was used primarily to rank reservoir favorability, the RFC thresholds were chosen based on the distribution of RFC for the entire reservoir population. The distribution of RFC across the entire basin is strongly left-skewed, and therefore is better illustrated on a semi-log plot (Figure 1). The RFC thresholds were chosen based on a logarithmic scale, base ten. RFC values range from 0.003–15500 mD-m, and thresholds were placed at 1000, 100, 10, and 1. Reservoirs with RFC greater than 1000 mD-m are deemed most favorable.

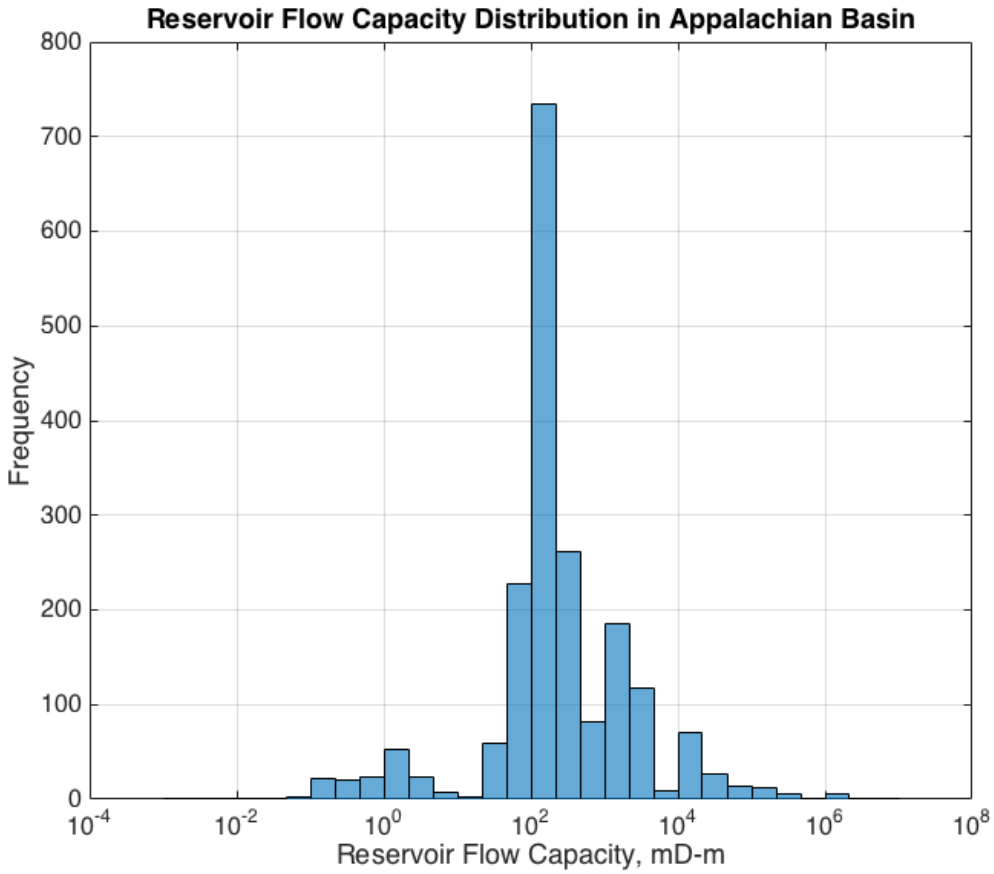

Figure 1. Distribution of average Reservoir Flow Capacity for all natural reservoirs in the Appalachian Basin.

5.2. Reservoir Productivity Index Thresholds

RPI_g and RPI_w metrics thresholds were chosen based on information regarding economic productivity rates published in the geothermal literature.

5.2.1. RPI_w Thresholds

Agemar et al. (2014) report that pressure drawdown for sedimentary geothermal systems typically range between 1-3 MPa. If we assume the greatest pressure drop of 3 MPa, and assume that 30 kg/s is the minimum mass flow rate acceptable for the water-based system, our RPI_w threshold for the reservoir which would not require stimulation (i.e. no EGS) is approximately 10 kg/MPa-s. Because the distribution of RPI_w in the basin is

strongly left-skewed, the remaining thresholds are logarithmic: 10, 1, 0.1, 0.01. Reservoir enhancement techniques can improve productivity by six to nine times (Cladouhos et al., 2014; Cho et al., 2015), so reservoirs in the 10–1 kg/MPa-s may be suitable with EGS.

5.2.2. RPI_g Thresholds

The thresholds for RPI with sCO_2 as the working fluid were determined using the thresholds for RPI_w as a baseline, which needed to be adjusted to normalize for the amount of heat extracted. For direct use heat applications, the difference in required mass flow rate of sCO2 instead of water should only be related to the difference in heat capacity. According to Chen and Lundqvist (2006), the heat capacity of sCO2 is about 4 kJ/kg-K, assuming the CO_2 is maintained at a constant pressure of 10 MPa and an average reservoir temperature of 60 ºC. At equivalent temperatures, the heat capacity of water is 4.2 kJ/kg-K. These values are very close, therefore the same thresholds were applied to RPI_g.

5.3. Thresholds for the Coefficient of Variation

The Coefficient of Variation of the RPI ranges from 0.08-0.39. The thresholds were selected using equal interval groups, in order to best illustrate relative uncertainty across the reservoir population in the basin. The thresholds selected are: 0.14, 0.20, 0.27, and 0.33.

6. Selection of Most Favorable Reservoirs

In order to isolate the reservoirs that have the highest potential productivity with the least risk, the RPI or RFC can be combined with the CV results, depending on the desired outcome. If the interest is reservoirs that have a high predicted productivity, RPI can be used; whereas if the interest is in highlighting reservoirs with the most ideal geologic properties, RFC can be used. For the RPI_g and RPI_w maps, reservoirs with an RPI greater than 10 kg/MPa-s and with a CV

lower than 0.25 (25% uncertainty) were selected as the most favorable reservoirs. For the RFC map, reservoirs with an RFC greater than 100 mD-d and with a CV lower than 0.25 were selected as the most favorable reservoirs. The selected reservoirs with the highest potential but a greater risk can also be isolated for further research to better constrain and quantify the risk.

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