Methods for Assessing Opportunities for Ring Dam Pumped Storage Hydropower

Evan Rosenlieb,[1] Victor Igwe,[1] Lindsay Ashworth,[2] Vignesh Ramasamy,[1] and Stuart Cohen[1]

1 National Laboratory of the Rockies
2 Small Hydro Consulting, LLC

The National Laboratory of the Rockies is a national laboratory of the U.S. Department of Energy, Office of Critical Minerals and Energy Innovation, operated under Contract No. DE-AC36-08GO28308.

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NATIONAL LABORATORY OF THE ROCKIES

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List of Acronyms

ANU	Australia National University
FERC	Federal Energy Regulatory Commission
GL	gigaliter
GW	gigawatt
GWh	gigawatt-hour
kW	kilowatt
MW	megawatt
NLR	National Laboratory of the Rockies
NREL	National Renewable Energy Laboratory
PSH	pumped storage hydropower
RCC	roller-compacted concrete
TW	terawatt
TWh	terawatt-hour

Executive Summary

There is growing interest in new pumped storage hydropower (PSH) deployment to provide a range of grid flexibility, reliability, and resiliency services under an evolving and uncertain future power sector. The National Laboratory of the Rockies develops open PSH resource assessment and cost modeling tools to help evaluate PSH deployment opportunities. This report describes expansions to those tools to consider an additional PSH system configuration—ring dam reservoirs built on flat topographical features that are constructed from roller-compacted concrete material. This reservoir type is common among current PSH proposals and requires new methods to identify sites with this reservoir geometry throughout the United States and characterize the associated dam cost. Cost characterization for ring dam reservoirs required collecting historical dam cost data for earthen, rockfill, and roller-compacted concrete dams and regressing equations that relate costs between alternative materials.

The ring dam site identification algorithm follows a five-step procedure:

1. Individual contiguous patches of suitable area are identified using a connected component labeling algorithm.
2. Small, fragmented areas of unsuitable area within large patches of suitable area are removed using a morphological closing algorithm because they are considered unlikely to have a significant impact on the suitability of a potential ring dam reservoir.
3. The distance for each pixel within the contiguous suitable area to the closest edge of the contiguous suitable area is calculated using a chamfer distance transformation algorithm.
4. The pixel with the maximum distance is identified as the center of the largest possible circle that can fit within the suitable area.
5. A circular geometry is generated from this origin point representing the optimized reservoir size and location.

Once ring dam reservoirs are identified, they are then paired with potential dry-gully reservoirs, and the full set of potential paired reservoirs is cost-optimized to produce a least-cost set of potential PSH sites with no overlapping reservoirs. The resulting analysis found 1,663 ring-dam-to-dry-gully systems in the contiguous United States that are lower cost than any overlapping dry-gully to dry-gully systems, 29 in Alaska, and none in Hawaii or Puerto Rico. These systems constitute 1.5 terawatts of capacity in the contiguous United States and nearly 29 gigawatts in Alaska, demonstrating that, under suitable topography and head, ring dam systems can provide cost-effective PSH opportunities. The greatest density of these opportunities is found in the Intermountain West, where there are mesas and flat land at bases of mountain ranges, but continued work could incorporate additional site characteristics or consider more complex reservoir shapes to find additional PSH deployment opportunities.

Table of Contents

List of Figures

List of Tables

1 Introduction

Utility-scale energy storage is increasingly viewed as a key technology for providing electric grid flexibility, reliability, and resiliency. Storage technologies can reduce power system operating costs by enabling thermal resources (fossil and nuclear) to operate more efficiently while also balancing variable resources (wind and solar). They also contribute valuable ancillary services that help maintain stable and reliable grid operation (Mongird et al. 2020; Koritarov et al. 2021). Although the majority of recently deployed utility-scale storage consists of lithium-ion battery technologies with up to 4 hours of storage duration, pumped hydropower storage (PSH) still constitutes 96% of utility-scale energy storage capacity and 70% of the rated power capacity of utility-scale storage systems (EIA 2025; Uria Martinez and Johnson 2023). PSH remains the only long-duration (10+-hour) storage technology widely deployed at utility scale. Although only one small new facility has been commissioned since 1995 in the United States, there is growing interest in developing new PSH sites as indicated by the Federal Energy Regulatory Commission (FERC) permitting pipeline (Uria Martinez and Johnson 2023). Interest in PSH is growing alongside substantial battery investment because it is more cost competitive at longer durations and has unique advantages for providing inertia, voltage support, frequency stability, and black-start capability. Some of these operational advantages can be further enhanced by using variable speed or other advanced pump designs.

The National Laboratory of the Rockies (NLR) develops open data and tools and executes modeling and analysis to support a broader understanding of PSH opportunities and trade-offs. Two such products are the PSH cost model and the PSH resource assessment. The PSH resource assessment uses the cost model to develop technical PSH potential and cost estimates for tens of thousands of sites across the United States, including Alaska, Hawaii, and Puerto Rico. To date, NLR's PSH resource assessment has considered the following site configurations: (1) closed-loop PSH with two dry-gully reservoirs, (2) add-on PSH where one new dry-gully reservoir is paired with an existing reservoir, and (3) pit mines that could be converted into PSH reservoirs. "Closed-loop" refers to a site where neither reservoir intersects with an existing waterway, although the authors (we) make no assumptions about the source of reservoir fill water.[1] A dry gully is a topographic feature that uses a naturally occurring gully, valley, or canyon-like feature to form part of the water impoundment structure, which greatly reduces the amount of dam construction required for a given water volume.

The cost model was also initially designed to only consider earthen embankment dams. This is expected to be most cost-effective for many dry gullies and provides a conservative cost approximation for rockfill dams in sites where locally available rock is used as some or all of the required dam volume to reduce the new material required for the dam. Pit mine opportunities are not included in the PSH cost model because of high cost uncertainty. The resource assessment of PSH systems in the United States solely using dry-gully and existing reservoirs found there is a large amount of new closed-loop and add-on PSH potential, particularly in the highly mountainous western contiguous United States region (CONUS). This assessment demonstrates

[1] The PSH cost model does allow the user to manually enter a cost for fill water, if that cost is expected. Future versions are also planned to include a cost component for reservoir liners based on forthcoming work by Oak Ridge National Laboratory (DeNeale et al., n.d.).

these efficient locations for reservoirs are, by themselves, sufficient for the identification of new potential PSH locations.

Although the site configurations and materials considered so far in the NLR resource and cost assessment encompass a large fraction of possible new PSH in the United States, several proposed facilities, many of which are well into the FERC licensing process, instead use “ring dams,” where a fully enclosed dam structure is constructed on relatively flat topographical features. Ring dam sites can benefit from maximizing potential head height, improving overall cost-effectiveness. Because most potential dry-gully reservoirs are located on the slopes of mountainous areas, paired systems using only dry-gully reservoirs are often formed by joining two potential reservoirs at different elevations along the same or neighboring slopes. The constraint of being located on sloped terrain means that flatter areas at lower elevations at the bottom of such slopes or at higher elevations on the top of mesas or bluffs remain unexamined, although they may provide an opportunity for PSH systems with higher hydraulic head and lower costs.

Further, proposed ring dam reservoirs are often planned to use roller-compacted concrete (RCC) as the dam material either for the full dam volume or as a facing for a rockfill dam because this construction reduces dam material quantity needs, albeit at a higher material unit cost. Because dams must encircle the entire reservoir in ring-dam-type reservoirs, the large volumes required for earthen dams can lead to earthen ring dams requiring particularly high dam excavation volumes and lower reservoir volumes because of volume that is instead consumed by the dam infrastructure. For example, the proposed Goldendale, Seminoe, and White Pine PSH plants all use ring dams for at least one new reservoir (FFP Project 101 LLC 2020; Black Canyon Hydro LLC 2023; White Pine Waterpower LLC 2023). Seminoe plans include use of RCC to construct a new upper reservoir that connects to an existing lower reservoir, and Goldendale, White Pine, and Gordon Butte all plan to use RCC-faced rockfill dams (Black Canyon Hydro LLC 2023; FFP Project 101 LLC 2020; White Pine Waterpower LLC 2023; Absaroka Energy LLC 2022).

Given clear industry interest in PSH facilities with these configurations, it became important to expand the NLR tools and algorithms to characterize ring dam opportunities for PSH and calculate the costs of dams that might use rockfill or RCC as the dam fill material. The rest of this report describes the methods and outcomes NLR is using to accomplish these expansions. We describe the geospatial algorithms developed and implemented to identify ring dam reservoir opportunities on flat topography features throughout the United States, including Alaska, Hawaii, and Puerto Rico. Then we present the PSH cost model expansions to consider alternate dam material types, namely rockfill and RCC. These two components are then integrated into the complete PSH reservoir pairing and siting workflow to produce a first-of-its-kind national resource and cost assessment of PSH sites that utilize ring dams for one or more reservoirs. Results are presented as geospatial datasets and supply curves that can be used by a variety of other modeling and analysis tools to evaluate PSH deployment opportunities.

This work aims to complement prior data and analysis and produce a more complete picture of the PSH landscape in the United States. It lays the groundwork for similar evaluations at alternate scales, scopes, and locations throughout the world.

2 Ring Dam Resource Assessment

Assessing technical potential for ring dam reservoirs includes first finding all possible locations where ring dams could exist, then identifying a set of potential reservoir pairs that use ring dams. These procedures incorporate practical technical limitations validated through literature, physical relationships, and hydropower industry stakeholder engagement.

2.1 Identifying Potential Ring Dam Locations

The algorithm to detect areas that may be suitable for the construction of ring dams is inspired by the algorithm for such sites used by researchers at Australia National University (ANU), who describe them as "turkey's nest" dams (Andrew Blakers et al., n.d.). The general method of the ANU algorithm is as follows:

- Divide the input digital elevation model[2] into tiles large enough to create a usable reservoir at feasible dam heights. As originally described, this was 360-meter-by-360-meter (m) tiles.
- Calculate the maximum dam height and the dam volume required to store 1 gigaliter (GL) of water by modeling the construction of a ring dam around the perimeter of this tile.
- Filter these potential areas based on maximum dam volume and maximum dam heights (values of 600 million liters and 20 m are originally described). The areas that meet these criteria minimize the amount of dam construction needed to impound the same amount of water, which indicates the underlying topography is viable for ring dam construction, generally because that location is flat or concave.

Although the concept of modeling ring dams at different locations and using the efficiency of the dam-to-water volume ratio as a measure of site suitability remains the underlying basis of our algorithm, modifications were made to meet the context of the NLR resource assessment. Primarily, the 1-GL water volume reservoirs considered by the ANU algorithm are not very large relative to the PSH systems that the NLR resource assessment typically focuses on. With system power-generating capacities produced by the resource assessment generally being in the hundreds of megawatts to multiple gigawatts in size, a reservoir with a volume of 1 GL would require very large head heights to form a system in this range of capacities. For instance, a reservoir of 1 GL water volume would require a net head of more than 490 m to produce a 100-megawatt (MW) capacity plant with 10 hours of storage assuming a usable water volume of 85% and a generator efficiency of 88%. Because this represents approximately the first percentile of generation capacities produced in prior PSH resource assessment for the United States, it became necessary to develop an algorithm to search for larger volume reservoirs to evaluate ring dams that would more likely produce generating capacities in the desired range.

To examine how larger areas or taller dam heights could produce reservoirs of a more compatible size with the reservoirs and systems previously produced, the ring dam search algorithm was run over CONUS with varying dam radii and heights. However, in the algorithm as originally described in the ANU paper, increasing the dam radius results in larger tiles being

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[2] A digital elevation model is a representation of the Earth's topographic surface, excluding any surface objects and including vegetation and buildings. https://www.usgs.gov/faqs/what-a-digital-elevation-model-dem.

used in the input elevation model, therefore decreasing the sampling density. Sampling the landscape at a lower density for larger-radius reservoirs would artificially decrease the number of viable reservoirs relative to smaller-radius reservoirs; therefore, a modification was required to compare reservoirs of different radii with each other at the same sampling density. A moving window approach was adopted, where a potential reservoir is modeled as centered around each individual raster pixel, as opposed to the previous tiled approach, which models a reservoir for each 360-m-by-360-m tile.

Moving window functions do require the use of odd-numbered pixel windows because creating a symmetric window around a given pixel requires the center pixel to be included along with an equal number of pixels in both directions. As such, the length of the window (W) in both the x and y dimensions follows this form as a function of search radius (r):

$$W = 1 + 2r$$

With an input pixel size of 30 m^2, this means the 360-m^2 windows of the ANU algorithm were not possible to replicate. Window sizes of 330, 390, and 450 m^2 were thus chosen so that the 360-m^2 window remained within the range while also exploring the impact of larger sizes. Dam heights of 20, 30, 40, 50, and 60 meters were used in combination for each window size. We examined the number of reservoirs created for each combination of dam radius and height that met the criteria of being at least 3 GL in volume, as this is approximately the first percentile of reservoir volumes seen in previous resource assessments. The count in thousands of reservoirs for each combination is shown in Table 1.

Table 1. Count of Reservoirs for Each Analyzed Combination of Dam Height and Window Size

Counts are in millions.

	20-m Dam Height	30-m Dam Height		40-m Dam Height	50-m Dam Height	60-m Dam Height
330-m Window	0	0		0	0	<1
390-m Window	0	0		10.5	36.7	25.4
450-m Window	0	13.0		33.6	41.4	45.6

Even in locations that provide the most ideal concave topography for the construction of a ring dam, the volumes of water required for feasibly sized systems are not seen for the 20-m dam height nor (except for rare exceptions) the 330-m window sizes. This suggests some combination of larger radius and dam height is necessary to generate acceptably sized reservoirs. However, for ring dams where the dam circles the entirety of the reservoir, using higher dam heights very quickly lowers the ratio of reservoir water volume to dam excavation volumes required. This ratio for a hypothetical ring dam reservoir built on perfectly flat land for each radius and dam height is shown in Table 2**Error! Reference source not found.**. Note the dam volume calculation uses NLR's cost model formula for total dam excavation volume for an earth fill dam, including the excavation and grouting of the core trench and impervious core foundation and all other earthwork required; therefore, it represents a significantly greater volume than the above-ground fill volume of the dam (Cohen et al. 2023). This leads to lower ratios than may be expected. Although these numbers display ratios for earthen dams, the relationship holds for other materials considered.

Table 2. The Ratio of Reservoir Water Volume to Dam Excavation Volume for Each Analyzed Combination of Dam Height and Window Size, Assuming a Ring Dam Built on a Perfectly Flat Area

	20-m Dam Height	30-m Dam Height	40-m Dam Height	50-m Dam Height	60-m Dam Height
330-m Window	0.68	0.55	0.45	0.39	0.34
390-m Window	0.84	0.68	0.57	0.48	0.42
450-m Window	1.01	0.82	0.68	0.58	0.50

These ratios represent the lower bound of what would be expected from potential ring dam reservoirs, as the ideal location for such a reservoir includes concave topography that can increase the amount of water stored for a given dam height. However, it demonstrates the volume of excavation required to impound water becomes unacceptably high with higher dam heights. This implies the algorithm must maximize window size instead of dam height to identify reservoirs with sufficient volumes to form utility-scale PSH systems with generating capacities in the 100-MW or higher range, which is the focus of NLR's large PSH cost model and resource assessment.

One option to search for larger-radius reservoirs is to increase the window size of the moving window until the required reservoir volumes are found at smaller dam heights. However, there are two limitations to this approach. First, the moving window method's computational intensity increases as a function of the window size squared, meaning the computational requirements can quickly become intractable at larger window sizes. Second, although a larger window size may produce reservoirs with better water-to-dam ratios, there is no guarantee any one fixed window size creates the optimal reservoir size for a given location. Where possible, if there is more room for a larger-radius reservoir, the larger radius is preferable to using a taller dam height to achieve the same volume. Therefore, a better method would optimize the reservoir size instead of using a fixed window size.

To optimize reservoir size in any location, inspiration is taken from a previous paper that finds the maximum reservoir size that can fit into an arbitrarily shaped contiguous area of potential land available for reservoir development using a maximum inscribed rectangle algorithm (Görtz et al. 2022). This algorithm can find the single largest, compact geometry (in this case, a rectangle) that can fit inside of any arbitrary shape of suitable area for a reservoir. Although this accomplishes the goal of maximizing reservoir area for any location, there are two notable differences for use with NLR's other PSH resource assessment algorithms:

1. The algorithm as described in Görtz et al. (2022) uses vector representations of geometries instead of the raster representations used in the rest of NLR's reservoir identification algorithms. Vector processing generally, and the maximum inscribed rectangle algorithm specifically, are more computationally intensive than raster processing. Therefore, the algorithm is adapted to a raster form of the algorithm.
2. Given the decision to assume these dams are constructed from RCC material, which can easily be designed for curvilinear shapes, the algorithm is adapted to search for circular instead of rectangular reservoir geometries, which maximize the reservoir area for a given perimeter. Although actual reservoir shape will depend on a variety of site-specific design considerations to optimize dam-to-water volume and dam shape, circular geometries represent a base-case scenario to identify promising locations for further evaluation.

The steps of this raster algorithm are shown in Figure 1 and the list following. All algorithms described were used as implemented in the SciPy ndimage python package.

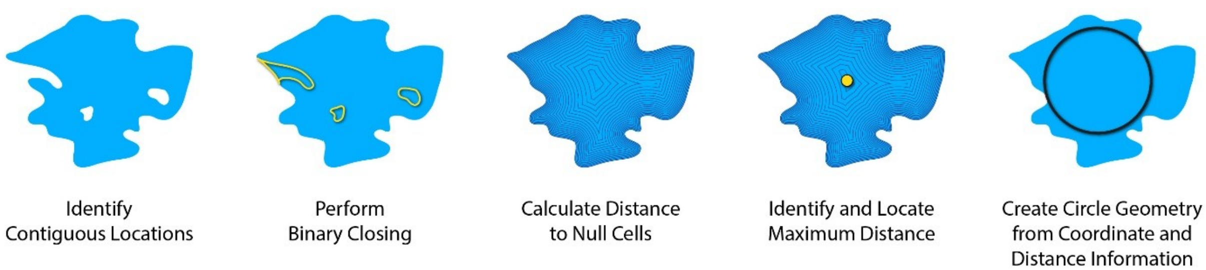

Figure 1. Ring dam size optimization procedure. ***Image by Billy Roberts, NLR***

1. Individual contiguous patches of suitable area are identified using a connected component labeling algorithm.
2. Small, fragmented areas (up to three pixels in width) unsuitable for siting that are within large patches of suitable area are considered as unlikely to have a significant impact on the suitability of a potential ring dam reservoir and are removed using a morphological binary closing algorithm.
3. The distance for each pixel within the contiguous suitable area to the closest edge of the contiguous suitable area is calculated using the exact euclidean distance transformation algorithm (Maurer et al. 2003).
4. The pixel with the maximum distance is identified as the center of the largest possible circle that can fit within the suitable area.
5. A circular geometry is generated from this origin point, representing the optimized reservoir size and location.

The input raster of suitable areas, defined here as areas exhibiting flat or concave topography, is generated using the fixed window algorithm with a 450-m^2 window size to identify pixels where the elevation of the interior area of the reservoir is equal to or lower than the elevation of the perimeter. An example of the input suitability raster and the final, optimized reservoir geometries created for a sample area is shown in Figure 2.

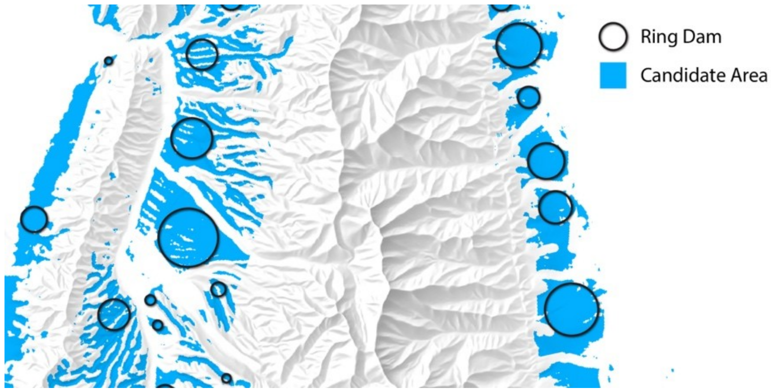

Figure 2. Sample area demonstrating how ring dam reservoirs are identified from suitable areas within a given window area. ***Image by Billy Roberts, NLR***

Final reservoir parameters are then calculated for each optimized ring dam reservoir geometry. First, reservoirs in which the perimeter's average elevation is not equal to or higher than the reservoir's interior average elevation are removed—this means the larger optimized reservoir area no longer meets the criterion of being on flat or concave land. The number of size-optimized reservoirs that no longer met this criterion represented 13.8% of all reservoirs found by the algorithm, showing that the method of finding large areas of flat or concave topography from contiguous areas of smaller flat or concave topography usually correctly identifies areas that still meet this criterion. Second, as with the dry-gully reservoirs, reservoir geometries that spatially intersect with geospatial datasets representing incompatible land uses are excluded from consideration. Although different assumptions for land use incompatibility are considered in the full resource assessment dataset, the least restrictive scenario is shown in the results of this report. Other scenarios apply additional exclusions such as ephemeral waterways, major roads, and prime agricultural land. A description of the land use filters applied for results shown in this report and their sources is found in Table 3.

Table 3. Land Uses Excluded From Reservoir Construction

Exclusion	Data Source
Existing water bodies and waterways	National Hydrography Dataset (NHD) (US EPA 2018)
Protected federal lands	Esri Federal Lands dataset (Esri 2025b)
Urban areas and towns	Global Human Settlement Layer (GHSL) (Schiavina et al. 2023)
Critical habitats for endangered species	U.S. Fish and Wildlife Service (FWS) (USFWS 2025)
Wetlands (with 1,000-foot buffer)	National Land Cover Database (USGS 2020)
Permanent snow/ice	National Land Cover Database (USGS 2020)
Wetlands (with 1,000-foot buffer; Alaska, Hawaii and Puerto Rico)	Esri Global Land Use Land Cover (LULC) dataset (Esri 2025a)
Permanent snow/ice (Alaska)	Esri Global LULC dataset (Esri 2025a)

The estimated water volume for each reservoir geometry is calculated as follows:

$$V = A \cdot \left(H + E_p - E_i\right)$$

where:

V is the water volume of the reservoir

A is the reservoir geometry area

H is the assumed dam height

E_p is the average elevation of the perimeter of the reservoir geometry

E_i is the average elevation of the interior of the reservoir geometry

As with dry-gully reservoirs, multiple dam heights for each location are modeled. With an initial estimate of reservoir volumes with dam heights from 10 m to 40 m and a comparison with the volumes of dry-gully reservoirs, a 20-m dam height was shown to produce reservoirs with volumes that most closely matched the distribution of reservoir volumes seen in dry-gully reservoirs. A steep decline in the similarity of volume distribution was seen such that 10-m dam heights produce smaller reservoir volumes, with only a minority having similar volumes as dry-gully reservoirs, and 30-m dam heights produce larger reservoir volumes with a minority having similar volumes as dry-gully reservoirs. Therefore, dam heights of 15, 20, and 25 m were chosen for the ring dams in this study.

This procedure ultimately results in 72,777 ring dam reservoir locations and 218,331 potential reservoirs with each of the three dam heights being modeled for each location within CONUS. This represents significantly fewer reservoir locations than the more than 1.7 million dry-gully reservoir locations currently identified by the model for the same extent. This result is attributed to two differences between the algorithms used for the respective reservoir types. First, the ring dam reservoirs are currently only being identified in areas where they are close enough to be joined with existing dry-gully reservoirs, which greatly reduces the overall area available for siting them. Second, the dry-gully algorithm produces a dataset of reservoir geometries that is highly self-intersecting (a reservoir formed by placing a dam at the base of a gully will intersect with reservoirs formed by placing a dam further upstream on the gully), whereas the ring dam algorithm produces a dataset of reservoir geometries where no reservoir spatially intersects any other reservoir.

2.2 Finding Paired Ring Dam Systems

The primary goal when identifying sites for new potential ring dams is to pair with previously modeled dry-gully reservoirs. This enables the use of efficient reservoir dry-gully locations with the potential for higher head height systems from pairing with a ring dam on a flat area. In the right location, two ring dams may present the opportunity for an attractive PSH location without using a dry-gully-type reservoir at all. However, because of the computational intensity of running the ring dam algorithm for every potential location across the United States, it was necessary to prefilter ring dam locations strictly to areas where they could be paired with the previously identified dry-gully reservoir locations, and only ring-dam-to-dry-gully pairings were considered for this assessment. The potential for computational improvements that would allow for the assessment of all possible ring-dam-to-ring-dam pairing presents a possibility for future work.

As recommended by NLR's cost model, the maximum gross head height assumed viable for single-stage reversible Francis turbines is assumed to be 750 m, and the maximum ratio of the water conveyance length (L, in both the horizontal and vertical direction) to the hydraulic head (H) that is assumed to be economically viable is 12:1 (or an L:H ratio of 12). This represents a significant change since the first iteration of the resource assessment, in which there was no maximum head limitation and a more lax L:H ratio of 15 was used, which we believe better represents technical and economic constraints of single-stage reversible Francis turbine systems (Rosenlieb et al. 2022). As a result, the maximum horizontal distance between any two reservoirs is 8.25 kilometers (km). This allows for the identification of potential PSH systems using one ring dam reservoir and one dry-gully reservoir by using a spatial join between ring dam reservoir geometries and dry-gully reservoir geometries with a maximum search distance of 8.25 km. All combinations of dam heights are available for pairing. Joined systems are then filtered to ensure they have gross heads between 200 and 750 m, L:H ratios between 4 and 12, and a maximum absolute water volume difference between reservoirs of 10% to arrive at the final dataset of all potential PSH systems to align with allowable design ranges from previous work (Rosenlieb et al. 2022).

3 Ring Dam Cost Assessment

The methods described previously produce potential PSH systems with an assigned water volume, gross head, and horizontal distance. Although this is enough to estimate critical parameters of the system such as the potential energy storage in megawatt-hours and the generation capacity in megawatts for different assumed storage durations, dam excavation volume must also be determined to estimate the system costs. The methods previously used to estimate dam excavation volume and costs for dry-gully reservoirs assume earthen embankment dams. Although this is a common type of dam used for small reservoirs on flat land, ring dams are more likely to use rockfill or RCC, as discussed previously. Without specific information available about the geological context of any individual PSH site, RCC is chosen as the default assumed material for ring dam reservoirs, as it is less dependent on local availability of fill material and is more likely to represent a conservative estimate of dam construction costs. However, methods to estimate volume and costs for both rockfill and RCC dams are pursued to allow cost estimation for rockfill dam structures where appropriate.

3.1 Concrete Dam Volume Calculation

In the ring dam identification algorithm, each reservoir has an associated dam length and average dam height. This allows for a similar dam volume calculation as used for earthen embankment dams: first, average volume per linear section is calculated as a function of height, and then this value is multiplied by the dam length to get total dam volume. However, different dam materials are known to have different required widths and volume per linear section, requiring different formulas to calculate volume per linear unit as a function of dam height.

We use literature on dam construction techniques as a reference for the relative volumes of all three dam material types, accounting for differences in slopes of the dam cross section (Bass 1991). Although formulas are not directly given in the publication, points along the curves in Figure 2 from Bass (1991) were digitized and fitted with second-degree polynomial equations with R-squared values above 0.99 for all three curves, suggesting this method was able to reproduce the formulas with high fidelity. The given formula for earthen dams is different than the formula given in the EPRI PSH evaluation guide that NLR's cost model uses (EPRI 1990); to quantify the difference, volumes per linear foot were calculated for dam heights of 20, 40, 60, 80, and 100 m, which samples the range of dam heights represented in previous resource assessments. Across these five points, the maximum absolute difference in earthen dam volume expressed as percent difference from the EPRI formula was 19.8%, and the mean absolute difference was 11.8%. While the difference is not negligible and likely reflects some divergences in assumptions between the two models, such as dam batter ratios and crest widths, the difference does not suggest that fundamentally different definitions of volume are being modeled (for example, the above ground volume of the dam vs. the total excavation needed for construction). Therefore, the formulas for rockfill and RCC dams are considered broadly compatible with the assumptions of the NLR cost model. The EPRI formula for earthen dam volume and the Bass formulas for all three materials are:

EPRI formula for earthen dams:

$$V_{Earth,EPRI} = 9.05 \cdot 10^{-5} \cdot h^2 + 3.86 \cdot 10^{-3} \cdot h + 7.07 \cdot 10^{-2}$$

Bass formulas:

$$V_{Earth,Bass} = 6.21 \cdot 10^{-5} \cdot h^2 + 1.70 \cdot 10^{-2} \cdot h - .741$$

$$V_{Rock,Bass} = 3.72 \cdot 10^{-5} \cdot h^2 + 9.93 \cdot 10^{-3} \cdot h - .417$$

$$V_{RCC,Bass} = 1.64 \cdot 10^{-5} \cdot h^2 - 1.55 \cdot 10^{-3} \cdot h + .202$$

where, for all equations:

V = volume in thousands of cubic yards

h = dam height in feet

3.2 Concrete Dam Cost Calculation

Our literature review did not find any published source that compares cost per volume for these three materials, so a sample of dam volume and cost values from public sources was used to analyze the relative costs of the three materials and determine unit costs for each. In the United States, volume and cost values for recently constructed RCC dams were available on the website for the Portland Cement Association ("RCC Dam and Spillway Tracker," n.d.). Additionally, the National Inventory of Dams (USACE, n.d.) was filtered for publicly owned dams of at least 50 feet in height and a construction date of 2000 or later to identify relatively recently constructive dams that may have published information on cost (dam volume is provided as part of the National Inventory of Dams dataset). Reported costs for dams on this list were individually checked via internet search.

This exercise resulted in data for 17 RCC, 7 earthen, and 3 rockfill dams after removing records in which reported costs were not disaggregated in enough detail (e.g., they included the demolition of the previous dam). Although the data available by the cement trade association website provided a usable sample of information on RCC dams, the number of earthen and rockfill dams was insufficient to confidently compare relative costs, particularly across the range of volumes needed. To include more data on earthen and rockfill material dams, published volume and cost data of Australian dams were included (Petheram and Mcmahon 2019), increasing the sample to 24 RCC, 30 earthen, and 37 rockfill dams, with ranges of volumes representative of the range of volumes produced by the resource assessment.

Lack of disaggregation of volume and cost values makes these data difficult to compare directly to the volume and cost formulae used in the NLR cost model. In particular, it is not necessarily clear if the reported volumes are the total excavation volume or the above-ground fill volume, or if the costs include reservoir liners. Therefore, instead of using these data to directly predict cost as a function of volume, they are instead used to understand the cost per unit volume of RCC and rockfill dams relative to a similarly sized earthen dam. This method allows for costs of RCC and rockfill materials to be calculated as an adjustment to the established cost formula already used for earthen dams. These relative costs are quantified via the following steps.

1. An inflation and exchange rate adjustment (as applicable) are applied to the data to standardize costs to 2022 USD values.

2. Ordinary least-squares regression models are fitted to predict costs as a function of volume values for each respective material. Raw values are log transformed on both axes to better fit the assumptions of the ordinary least-squares model, and problematic values are removed (points having too much individual influence on the model, here defined as having a Cook's distance above 4/n). R^2 values for the earthen, RCC, and rockfill fits are 0.73, 0.8, and 0.74, respectively.
3. Costs are estimated using these regression models for a range of volumes for each material.
4. Ordinary least-squares regression models are fitted to predict RCC and rockfill costs as a function of the cost of the equivalent-volume earthen dam, allowing for predicted RCC and rockfill costs to be linear transformations of the predicted earthen cost of the same volume. For RCC, the y-intercept of the linear model is fixed to 0 to prevent an otherwise negative y-intercept that could produce erroneous cost estimates for low-volume dams.

The resulting formulas of this process are:

$$C_{RCC} = 11.389 \cdot C_E$$

$$C_{RF} = .787 \cdot C_E + 39.7$$

where:

C_{RCC} = Cost of an RCC dam in millions of 2022 USD

C_E = Cost of an earthen dam in millions of 2022 USD

C_{RF} = Cost of a rockfill dam in millions of 2022 USD

Note that the slope coefficient for rockfill dams is less than one, meaning large rockfill dams can be more cost-effective than large earthen dams. This may be an unexpected result, as rock is heavier per unit volume This phenomenon can be seen in the plot of the original data in Figure 3 and as such is not an artifact of the methods used. We believe this is likely a result of availability of materials; large rockfill dams will generally be built where there is local availability of suitable fill material, which is highly site dependent.

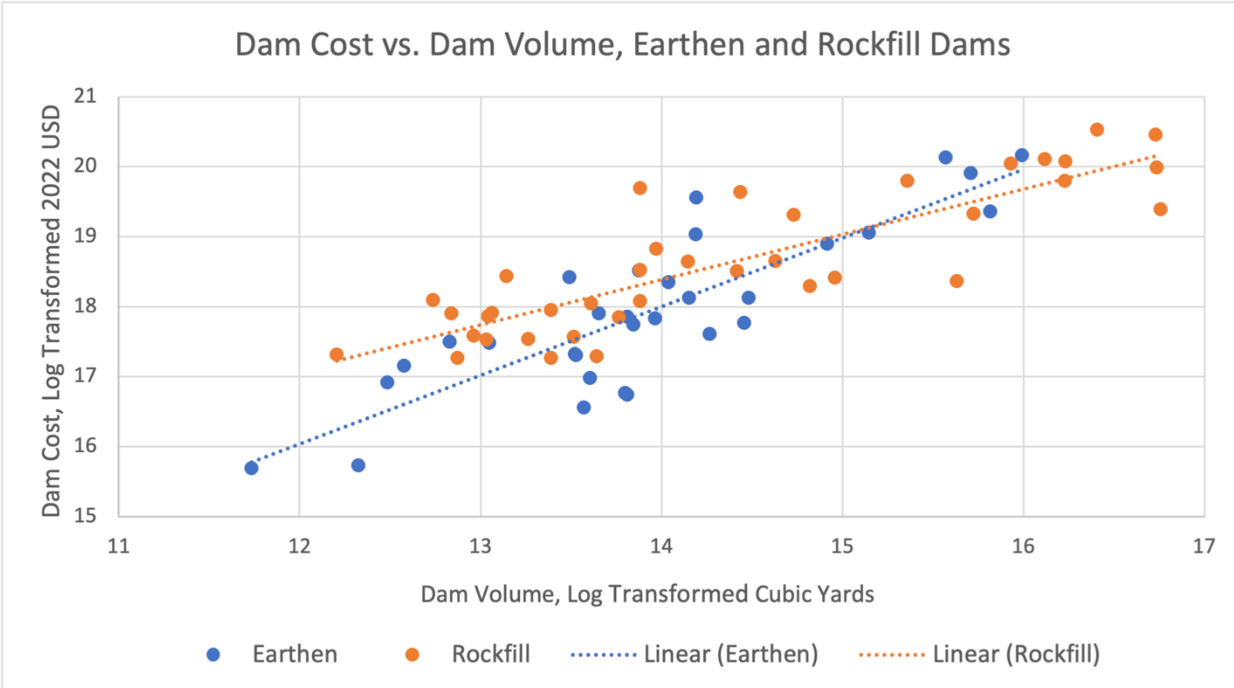

Figure 3. Dam cost-volume relationship for earthen and rockfill dams after a log transformation

4 Ring Dam Supply Curve Results

With the ability to calculate dam volumes and costs for ring-dam-type reservoirs using RCC dam construction, it is now possible to produce a cost-optimized set of potential reservoirs and compare cost distributions with systems previously identified using two dry-gully type reservoirs.

4.1 Finding Least-Cost Nonoverlapping Systems

Although the set of ring-dam-type reservoir geometries have no overlapping reservoirs, each geometry is modeled with three different dam heights. Additionally, each of these ring dam reservoirs may have the potential to form PSH systems with multiple other dry-gully reservoirs, which themselves overlap with other potential dry-gully reservoirs. To model how much capacity is realistically feasible, it is necessary to optimize the dataset of all potential PSH systems to ensure no PSH system is being modeled in a location already being used for a different PSH system. In other words, a nonoverlapping dataset of the lowest-cost PSH system that can be built in any given location must be produced from the dataset of all possible PSH systems that can be built in each location.

This least-cost nonoverlapping dataset is produced using a simple optimization algorithm. First, the cost in 2022 USD per kilowatt of capacity is produced for each possible system using the established PSH cost model with the modifications for RCC dam construction described previously (Cohen et al. 2023).(Cohen et al. 2023). Systems with costs exceeding $4,000/kW (2020 dollars; or $4,557/kW in 2022 dollars) are assumed to not be economically competitive with other energy storage technologies and are excluded from consideration. A spatial intersection is used to produce a lookup table of remaining systems that overlap with each other. All systems are ordered by cost, and the algorithm begins by choosing the lowest-cost system for inclusion in the nonoverlapping dataset. Using the overlap lookup table, all systems that overlap with this system are removed from consideration from the ordered list. This process is then repeated until no available systems are left in the list.

The set of systems after this procedure represents the least-cost nonoverlapping set of ring-dam-to-dry-gully pairings. The capacities and costs of these systems can now be compared to the corresponding dataset of dry-gully-to-dry-gully reservoir pairs. To understand where ring-dam-to-dry-gully paired systems provide a more attractive opportunity than dry-gully-to-dry-gully paired systems, ring-dam-to-dry-gully systems can be removed that spatially intersect with a lower-cost dry-gully-to-dry-gully system, therefore keeping only the systems that outcompete those found in the previous resource assessment.

4.2 Contiguous United States

A comparison of sets of the two system types for CONUS is shown in Table 4.

Table 4. Cost and Capacity Statistics

	Generation Capacity (MW)	Capital Cost ($/kW 2022)	Generation Capacity (MW)	Capital Cost ($/kW 2022)
System Type	Ring-Dam-to-Dry-Gully		Dry-Gully-to-Dry-Gully	
Count	4,486		37,425	
Mean	674	3,558	830	3,473
Minimum	180	1,736	195	1,560
5th percentile	297	2,400	394	2,393
1st quartile	405	3,073	609	2,995
Median	570	3,663	747	3,513
3rd quartile	783	4,091	1,003	3,997

In total, the thousands of ring-dam-to-dry-gully systems represent more than 3 terawatts (TW) of generation capacity and 30 terawatt-hours (TWh) of energy storage capacity assuming 10-hour storge duration. In general, ring-dam-to-dry-gully systems exhibit similar costs on a quantile basis to dry-gully-only systems. However, there are significantly fewer systems, and although still having an average generation capacity of more than 600 MW, the ring-dam-to-dry-gully systems show lower capacities across the distribution. This is likely primarily the result of the higher dam volumes required per unit of water of ring dam reservoirs, making systems less cost-effective for the high water volumes generally required for high-capacity systems. When system cost is plotted as a function of cumulative generation capacity to form a generation supply curve, as shown in Figure 4, the combination of fewer systems and smaller average capacity show that systems using ring dams are significantly more expensive for any given amount of cumulative generation capacity despite having similar costs on a quantile basis.

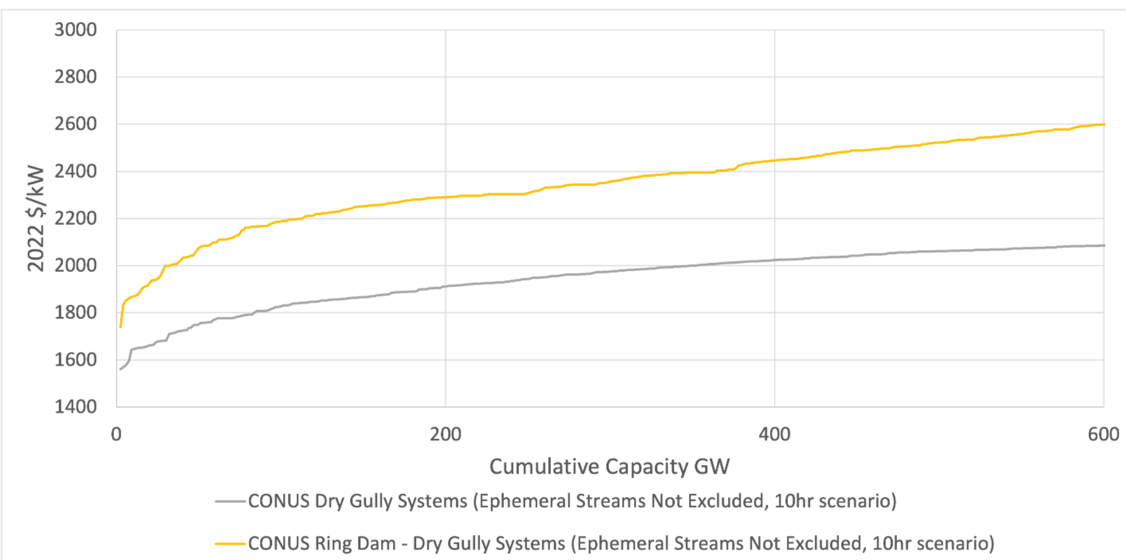

Figure 4. The first 600 gigawatts (GW) of the PSH supply curve for dry-gully-only systems and ring-dam-to-dry-gully systems

Although the systems using a ring dam reservoir have higher cost throughout their distribution, spatially intersecting layers of the two system types show there are locations where the ring dam systems offer a more promising opportunity compared to systems using solely dry-gully reservoirs. Out of the 4,486 systems, 1,312 ring dam systems are lower cost than the dry-gully systems they intersect with, and 919 of them have costs more than 10% lower. There are additionally 351 systems with costs below the $4,000/kilowatt (kW; 2020 dollars) cutoff and that do not intersect with a dry-gully-to-dry-gully system, representing new locations for PSH systems that did not show up in previous datasets. Although this total of 1,663 systems is significantly less than the more than 37,000 dry-gully reservoir-only systems, it does show that in areas with the right topography, ring dams could offer a lower-cost opportunity. These 1,663 systems represent a total capacity of 1.5 TW of generation capacity and 15 TWh of energy storage at 10 hours of duration.

The locations of these systems are shown in Figure 5.

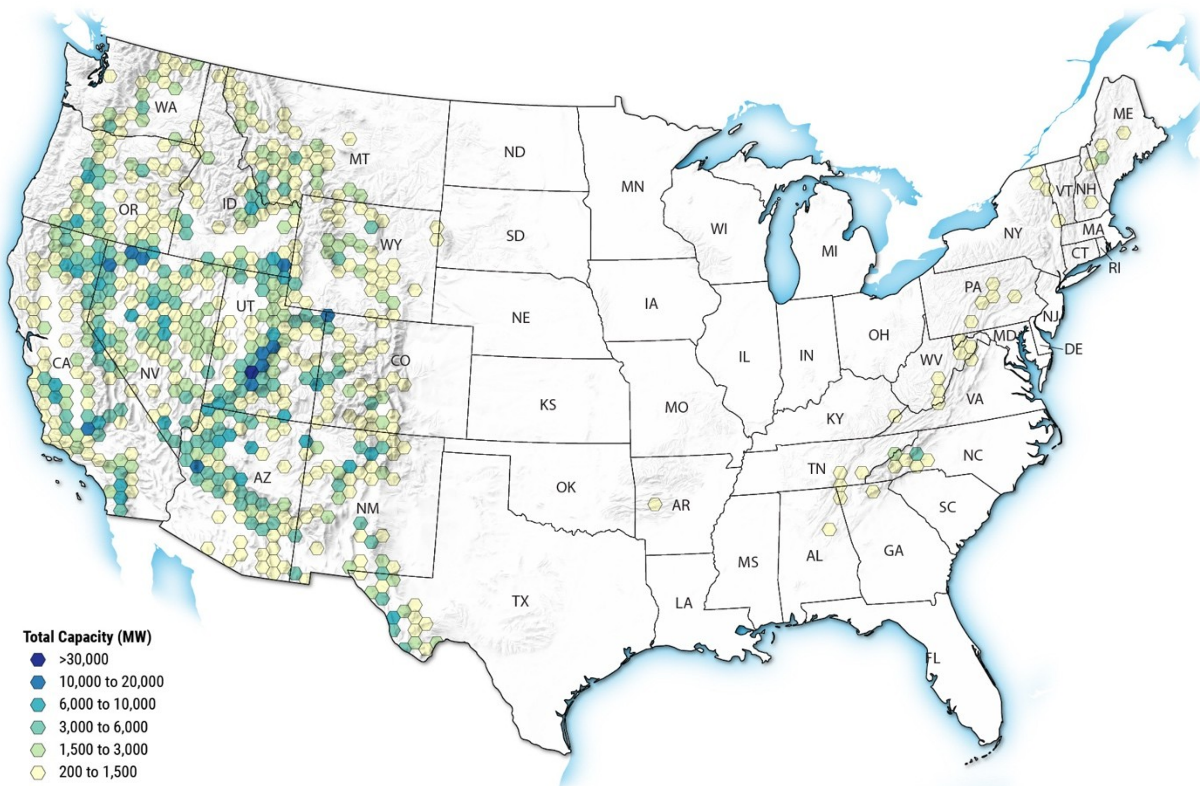

Figure 5. Map of ring-dam-to-dry-gully systems in CONUS. ***Image by Billy Roberts, NLR***

4.3 Alaska, Hawaii, and Puerto Rico

This ring dam algorithm is also applied to Alaska, Hawaii, and Puerto Rico. Previous NLR resource assessments using only dry-gully reservoirs have found potential systems in all three regions, although with a relatively small number of systems in the highly land-constrained regions of Hawaii and Puerto Rico (Rosenlieb et al. 2022). With ring dam reservoirs, which are most cost-efficient with larger areas and shorter dam heights, this dynamic is even more pronounced. The total number of ring dam reservoirs found in Alaska as part of this study is more than 93,000, whereas the numbers for Hawaii and Puerto Rico are 86 and 105, respectively. In Hawaii, four potential reservoir pairs using the ring dam reservoirs were identified in this study, but none were more cost-effective than overlapping systems using only dry-gully reservoirs. In Puerto Rico, where there is even less available head height, none of the identified ring dam reservoirs were able to form a system that met the minimum generation capacity of 80 MW assumed for the single-stage reversible Francis turbine systems. Although these results indicate large systems typically sought in CONUS are impractical for ring dam reservoirs in Hawaii and Puerto Rico, alternative design constraints and assumptions could lead to additional technical potential for PSH using ring dams in these regions.

In Alaska, this study identifies 149 systems in the least-cost nonoverlapping set of systems using a ring dam reservoir that are below the $4,000/kW (2020 dollars) cost threshold. Of these systems, 24 systems that overlap with dry-gully-only systems are more cost-effective (17 by more than 10%), which is a significantly lower number than seen in CONUS even when expressed as a percentage of dry-gully-only systems (0.4% vs. 4.4%). There are five additional systems that do not overlap with a dry-gully-only system and are below the $4,000/kW (2020 dollars) threshold. The reason Alaska produces so few potentially competitive systems using ring dam reservoirs may be differences in topography. In Alaska, the flat regions next to mountain ranges are often very land constrained by their proximity to the coast or by wetlands. The mountain ranges in Alaska also tend to produce fewer bluff- or mesa-like formations in which a ring dam could be used as an upper reservoir, particularly as compared to the Basin and Range geologic province in the Intermountain West of CONUS. Despite the limited number identified, the 29 systems identified still represent generation capacity of more than 28.8 GW and 288 GWh at 10 hours of duration.

5 Conclusion

This report describes a first-of-its-kind methodology and results from a national assessment of PSH technical potential that uses ring dam reservoirs paired with dry-gully reservoirs in the United States, including Alaska, Hawaii, and Puerto Rico. This effort required a novel algorithm to efficiently identify ring-shaped reservoir opportunities along with techniques to adapt earlier cost modeling work to accommodate dam construction with RCC and rockfill materials. These new capabilities allow ring dam reservoirs to be integrated into a more comprehensive overall PSH resource assessment that includes both ring-dam-to-dry-gully pairings and dry-gully-to-dry-gully pairings without any overlapping (and thus double-counted) reservoir opportunities.

Under typical design assumptions for large utility-scale PSH systems, the assessment found 4,486 potential ring-dam-to-dry-gully sites in CONUS, 149 in Alaska, 4 in Hawaii, and 0 in Puerto Rico. However, some of those sites use gullies that overlap with gully-gully pairings having lower capital costs, leaving 1,663 CONUS, 29 in Alaska, and 0 in Hawaii, where systems using ring dams present the best opportunity for PSH development. These lower-cost ring-gully sites constitute more than 1.5 TW of capacity in CONUS and more than 28.8 GW in Alaska. Dry-gully dam construction remains the most cost-effective approach in most cases, but results demonstrate there are attractive ring dam opportunities when the appropriate combination of topography and head is available. Our algorithm finds the greatest density of these in the Basin and Range province of the Intermountain West, a region notably high in mesas and flat land at the base of mountain ranges. The algorithm finds relatively few of these opportunities in other mountainous or hilly regions outside of the Basin and Range province, meaning that regions such as Alaska, Appalachia, and the Ozarks and Ouachitas primarily have dry-gully-to-dry-gully potential.

This technical potential and cost assessment builds on prior work to allow a more complete understanding of PSH opportunities and trade-offs in the United States. The resulting geospatial data can be readily used in energy systems modeling and analysis to further evaluate competitive market potential for PSH at spatial resolutions ranging from site-level to national scale. The methods could also be readily adapted and expanded to incorporate location- or region-specific factors and find yet more opportunities that are more aligned with practical considerations for that location. With several ring dam PSH opportunities already in development, this work allows the broader hydropower and power sector to go beyond a few known site assessments and identify new opportunities that ultimately enable a more holistic understanding of PSH potential in the United States.

6 Future Work

Although this work represents a significant step forward in modeling the full range of potential PSH system configurations available, future algorithm improvements could better represent ring dam reservoirs as generally constructed. One of the primary limitations of the systems using ring dams in this analysis is the cost-effectiveness of high-volume reservoirs compared to dry-gully reservoirs. Therefore, methods to better optimize ring dams for area or topographic concavity could help find more attractive ring dam reservoir sites.

Although the algorithm as described was successful in identifying large potential reservoir sites that are at least flat or somewhat concave, the reservoirs were only optimized for size. An algorithm that is able to jointly optimize both size and topographic concavity to minimize expected dam-to-water volume efficiency could produce lower-cost reservoir locations than optimizing for size alone. The available head and L:H ratio in an area could also be incorporated in this step, with areas having better head and L:H ratios allowing for less efficient dam geometries or vice versa. Additionally, the use of a simple geometry assumption for the shape of these reservoirs (a circle in the case of this analysis, or a rectangle in Görtz et al. 2022) allows for computationally efficient maximization of size, but larger reservoirs in any given location may be found by better shaping the reservoir to the constraints of the local topography. A combination of optimizing reservoirs for more than just size and the ability to consider other shapes—for example, by using clusters of smaller reservoirs to identify promising noncircular reservoir shapes—may be able to model reservoirs significantly better site-optimized for cost-to-water-volume efficiency.

Being able to co-optimize for size and shape could be of particular use to identify ring dam locations outside of the Intermountain West, as the algorithm shows a relative scarcity elsewhere of large, contiguous, and compact swaths of land that meet the condition of being perfectly flat or concave. For example, the Valley and Ridge province of Appalachia shares some similarity with the Basin and Range province in that it contains many ridges surrounded by relatively flat land. However, the slightly more variable topography of the valleys in the Valley and Ridge province do not provide as large of areas as the arid basins in the Basin and Range province of the Intermountain West: the 90th percentile of reservoir radius for reservoirs in Appalachia is 848 m, as opposed to 1044 m in the west of CONUS, which results in 50% more reservoir area. A more flexible co-optimization of size and shape may be able to identify good locations for ring dam reservoirs in the topography of this region where flat areas are not as compactly shaped.

Larger head heights are another way to increase PSH generation capacities when water volume is limited. With the assumption of single-stage reversible Francis turbine technology, head heights are limited to a maximum of 750 m, whereas potential sites of higher head are possible to find in the western CONUS. Francis turbine technology is the predominant technology used for utility-scale PSH in the United States and globally, but different technologies have been used for higher head height systems. For example, the Grand Maison hydroelectric plant in France uses multistage reversible Francis turbines to pump water up a head height of more than 950 m (Landry et al. 2022). Extensions to the NLR cost model to be able to represent these technologies could allow for the identification of these higher head height opportunities. Although this may be of primary interest for the water volume-limited ring dam reservoirs, this extension would apply to dry-gully reservoirs as well.

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