COMMENTS BY EPRI TO

ENVIRONMENTAL PROTECTION AGENCY

Docket ID: EPA–HQ–OLEM–2020–0107

Hazardous and Solid Waste Management System: Disposal of Coal Combustion Residuals from Electric Utilities; Legacy CCR Surface Impoundments; Notice of Data Availability
December 11, 2023

EPRI respectfully submits the enclosed comments on the U.S. Environmental Protection Agency's (EPA's) above-referenced notice of data availability.

EPRI is a nonprofit corporation organized under the laws of the District of Columbia Nonprofit Corporation Act and recognized as a tax-exempt organization under Section 501(c)(3) of the U.S. Internal Revenue Code of 1986, as amended, and acts in furtherance of its public benefit mission. EPRI was established in 1972 and has offices and laboratories located in Palo Alto, CA; Charlotte, NC; Knoxville, TN; Dallas, TX; Lenox, MA; and Washington, D.C. EPRI conducts research and development related to the generation, delivery, and use of electricity for the benefit of the public. As an independent, nonprofit organization, EPRI brings together its scientists and engineers as well as experts from academia and industry to help address challenges in electricity, including reliability, efficiency, health, safety, and the environment. EPRI also provides technology, policy, and economic analyses to inform long-range research and development planning and supports research in emerging technologies. As a tax-exempt research organization, EPRI makes its research results widely available to the interested public through publication, license, purchase, or other dissemination.

These comments reflect EPRI's mission and technical research results related to coal combustion product (CCP) management and environmental issues. The enclosed comments are EPRI's and do not reflect the opinions of those supporting and working with EPRI to conduct collaborative research and development.

EPRI hopes that its comments and technical feedback will be valuable to EPA.

Sincerely,



Neva Espinoza
Vice President, Energy Supply and Low-Carbon Resources

COMMENTS

U.S. Environmental Protection Agency

Hazardous and Solid Waste Management System: Disposal of Coal Combustion Residuals from Electric Utilities; Legacy CCR Surface Impoundments; Notice of Data Availability

Docket ID: EPA–HQ–OLEM–2020–0107

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1 Introduction

1.1 Background

On November 14, 2023, the U.S. Environmental Protection Agency (EPA) released a notice of data availability (NODA) pertaining to the Agency's May 18, 2023 proposed rulemaking on the Disposal of Coal Combustion Residuals (CCR) from Electric Utilities; Legacy CCR Surface Impoundments. This NODA made available an October 2023 draft risk assessment pertaining to legacy impoundments and coal combustion residual management units (CCRMU) proposed for regulation in the May 18th proposal.

EPRI has reviewed the 2023 draft risk assessment (2023 Draft RA) and is providing these comments to clarify one statement and provide scientific comments on a variety of items as summarized in Section 1.2 and explained with more detail in Section 2 of this comment package.

EPRI has been engaged in coal combustion product (CCP) research for more than 40 years and has developed a large knowledge base focusing on CCP characterization, management, and beneficial use; groundwater transport and risk; and remediation for situations in which a release to the environment occurs. Our research leaders—Bruce Hensel and Benjamin Gallagher—have more than 35 years of combined experience working on beneficial use, management, and environmental response issues associated with CCPs.[1]

1.2 Executive Summary

The purpose of these comments is to clarify one statement and to provide technical and scientific information for consideration by EPA with respect to the November 14, 2023 Draft RA.

All EPRI reports referenced in this document can be downloaded by the public at no cost from epri.com.

A list of comments is provided below. Please see the full comments in Section 2 of this document.

2.1 EPRI is an independent entity that performs energy-related research for public benefit. We respectfully request that EPA accurately describe EPRI as an independent research organization.

2.2 Comments on Problem Formulation (RA Section 2)

2.2.1 The presence of hydraulic head at one location does not demonstrate that flow is occurring. A hydraulic gradient between two connected points with different hydraulic head is required to drive groundwater flow. (Section 2.2.2)

[1] CCP and CCR both refer to fly ash, bottom ash, boiler slag, and solids captured from flue gas desulfurization (FGD) systems. EPRI uses the CCP terminology because it more closely aligns with our research on the beneficial use of these materials. The comments that follow use EPA's CCR terminology.

2.2.2 Using COALQUAL to predict bulk composition of coal combustion residuals is challenging and does not inherently result in improvements compared to using measured bulk compositions of coal combustion residuals. (Section 2.3.3)

2.3 Comments on Disposal Unit Groundwater Risk (RA Section 3)

2.3.1 The conclusion that facilities which were not previously modeled may pose "somewhat higher" risk is predicated on a visual observation concerning facility locations that is not clear and could be quantified. (Section 3.2)

2.3.2 The underlying data for Figure 3-2, showing modeled risk as a function of area and unit mass are not provided in the NODA or supporting documents, and without these data it is not possible to validate the results drawn from this figure.

2.4 Comments on CCRMU Groundwater Risk (RA Section 4)

2.4.1 The description of calculating bulk composition from COALQUAL data is ambiguous, and forces the reader to make assumptions to review the application. (Section 4.2.4)

2.4.2 The use of GSAsh in calculation of coal ash bulk composition from COALQUAL data is not supported by analysis to confirm it represents powerplant ash values, and overestimated trace element concentrations in powerplant ashes that contain unburned carbon. (Section 4.2.4)

2.4.3 The description of COALQUAL data filtering may contain a transcription error. (Section 4.2.4)

2.4.4 The COALQUAL filtering substantially reduced the number of western coal samples in the Draft RA and the validity of the filtering criteria to represent commercial coals was not evaluated. (Section 4.2.4)

2.4.5 Sampling of filtered COALQUAL data increased reliance on limited western and subbituminous coal data. (Section 4.2.4)

2.4.6 pH values in Figure 4-1 are not representative of field measured pH values for CCR porewater. This observation combined with the observation in Comments 2.4.7 and 2.4.8 makes the model predictions uncertain. (Section 4.2.5)

2.4.7 EPRI research has identified challenges using LEAF methods to predict porewater concentrations. Since EPA has a large field porewater dataset to draw from, and the 2023 Draft RA uses the field dataset for lithium, the modeling process would be more consistent, and results less uncertain, if the field porewater dataset was used for all modeled constituents. (Sections 2.3.4 and 4.2.5)

2.4.8 The leachate concentrations simulated for CCRMU in the 2023 Draft RA appear to be anomalously high for As, Mo, and Tl when compared to leachate concentrations measured in the field at CCR landfills, and as a result the risk for these constituents at CCRMU may be overstated. (Section 4.2.5)

2.4.9 The 2023 Draft RA model takes a more conservative approach to selecting the sampling locations and depths where model results are tabulated than the 2014 RA by narrowing the range of locations and depths and excluding effects of plume interception by surface water. No information is provided for the readers to understand how these differences from the 2014 RA affect predicted concentrations and resulting risk conclusions. (Section 4.2.8)

2.4.10 The modeling conducted for the 2023 Draft RA uses the single-value K_d approach for arsenic adsorption, which ignores the geochemical sensitivity of arsenic to variable groundwater conditions and does not meet current standards of practice. (Section 4.3, Table 4-2)

2.4.11 The 2023 Draft RA approach to MODFLOW modeling is constrained relative to the capabilities of the models used. Additional and more refined modeling can be performed using the same modeling approaches as described in the Draft RA. (Section 4.3)

2.4.12 The 2023 Draft RA did not provide sufficient data to evaluate the MODFLOW modeling. (Section 4.3)

2.5 Comments on CCRMU Fill Soil Risks (RA Section 5)

2.5.1 The assumption of a receptor living directly on top of a coal ash deposit is conservative. (Section 5.4)

2.6 Comments on uncertainty and Sensitivity Analysis (RA Section 6)

2.6.1 Radiological data are presented in terms of mg/kg, but the appropriate unit is pCi/g. (Section 6.1)

2.6.2 The effects of mining practices on calculation of bulk composition of coal combustion residuals from COALQUAL data were not considered. (Section 6.1.1)

2.6.3 Broad conclusions regarding the impact of coal processing on bulk content of coal combustion residuals calculated from COALQUAL data are not supported by data or analysis. (Section 6.1.1)

2.6.4 The higher infiltration with HELP version 4 versus version 3, depicted in Figure 6-1 does not necessarily indicate that the 2014 risk assessment underestimated risk.

2.6.5 The risk endpoints for radionuclides and non-radionuclides are different and not additive. (Section 6.2.2 and Figure 6-2)

2.7 Comments on Conclusions (RA Section 7)

2.7.1 The statement that historical and inactive units would also be expected to have risks even higher than previously modeled is not fully supported by the data provided. (Section 7.1)

2 EPRI Comments

2.1 EPRI is an independent entity that performs energy-related research for public benefit. We respectfully request that EPA accurately describe EPRI as an independent research organization.

On page 6-4, the 2023 Draft RA characterizes three EPRI reports as industry reports, and in the next sentence infers that EPRI is an "*industry partner*." These statements do not reflect EPRI's charter as a non-profit organization performing research for public benefit,[2] nor does it reflect EPRI's mission statement "Advancing safe, reliable, affordable, and clean energy for society through global collaboration, science and technology innovation, and applied research."[3] We respectfully request that EPA describe EPRI as an independent research organization rather than using the descriptions on page 6-4.

2.2 Comments on Problem Formulation (RA Section 2)

2.2.1 The presence of hydraulic head at one location does not demonstrate that flow is occurring. A hydraulic gradient between two connected points with different hydraulic head is required to drive groundwater flow. (Section 2.2.2)

On Page 2-4 the 2023 Draft RA states "*The hydraulic head from this water forces leachate into subsurface soils at a higher rate than can occur from gravity alone. EPA chose to model all surface impoundments during the active stage of their lifecycle under the assumption the constant presence of a hydraulic head would result in the highest releases*."

In groundwater hydrology, hydraulic head is the combination of elevation head and pressure head and is generally regarded as a form of potential energy (Freeze and Cherry, 1979). As a form of potential energy, hydraulic head can only cause water to flow (advection) when two areas of different head are connected. The difference in hydraulic head between the two connected locations is known as a hydraulic gradient. Advection is the primary mechanism for transporting solutes in groundwater, and as a central concern in the Draft RA, it is important for the Problem Formulation to recognize that a hydraulic gradient is required to drive flow, and the presence of hydraulic head at one location does not demonstrate a gradient is present or flow is occurring.

2.2.2 Using COALQUAL to predict bulk composition of coal combustion residuals is challenging and does not inherently result in improvements compared to using measured bulk compositions of coal combustion residuals. (Section 2.3.3)

The USGS COALQUAL database is a valuable resource, and EPRI has used data from COALQUAL in its research. However, using COALQUAL data to predict nationwide probabilistic distribution of trace elements in coal ash has challenges and does not necessarily result in an improvement over the 2014 dataset.

[2] See EPRI's articles of incorporation
[3] EPRI, 2023 accessible by the public at About EPRI

On Page 2-10 the 2023 Draft RA states that "*COALQUAL improves upon the previous constituent dataset for a number of reasons. First, the database includes a large number of geographically diverse samples collected from across 36 states. This provides confidence these samples adequately capture regional variability in coal quality. Second, the samples represent a composite of entire coal beds weighted by the thickness of each discrete interval of minable coal (or "bench"). This ensures the data are representative of broader coal quality from a mine and so less likely to be skewed by any isolated hotspots. Third, samples were collected by USGS and state agency partners, so there is no potential for bias toward individual facilities that might be more likely to provide samples for research. Finally, USGS has undertaken extensive data verification and validation efforts to ensure consistency and reliability of the database*."

The above four-point explanation has three weaknesses:

Point 1 identifies the large number of samples in COALQUAL as "*adequately capturing regional variability*" but no assessment was provided in the Draft RA to demonstrate that the large number of samples are representative of commercially used coal. Researchers who reviewed the use of COALQUAL data to estimate mercury content in powerplant feed coal found that COALQUAL significantly overestimates the mean mercury content in comparison to coal delivered to powerplants collected by EPA ICR. These researchers attribute the difference between COALQUAL and ICR coal data in part to the bias of COALQUAL toward Appalachian Basin coals (Kolker and Quick, 2014). Furthermore, because the COALQUAL database is not proportionally representative of coal consumption, filtering and weighting was used to represent commercial coal. Filtering and weighting COALQUAL reduces the power of the large dataset, and this limitation was not mentioned in Section 2.3.3. The Draft RA's approach to filtering and weighting is further discussed in comments 2.4.4 and 2.4.5.

Point 2 postulates that full bed thickness composite samples are less likely to be skewed by hot spots. However, this statement was not tested, for example by reviewing multiple samples from the same mine, seam, or basin.

Point 3 identifies the sample collectors, described in the Draft RA as "*USGS and state agency partners*" as less subject to bias than the dataset from "*individual facilities…more likely to provide samples for research*." However, biases within COALQUAL or the 2014 dataset do not appear to have been assessed in the Draft RA. Illinois, for example, produced 6% of total domestic coal since 1960 according to U.S. Energy Information Administration (EIA), but is represented by one sample in the filtered COALQUAL dataset. The COALQUAL database is itself a work of research and depends on collaborators such as land and mine owners granting permission for access to coal beds and coal samples.

Furthermore, the 2023 Draft RA's discussion of the use of COALQUAL data in Section 2.2.3 omits any mention of the significant challenges associated with developing bulk concentrations for ash from coal resource characterization data. Since coal resources in the ground must be mined, processed, transported, and combusted before the CCRs are produced, estimates of CCR bulk content must account for transformations of coal in each of these processes. After the COALQUAL data is adjusted to account for the impacts of mining, processing, and combusting on ash composition, the data must then be adjusted or weighted to account for differences

between the database population and commercial coal consumption to produce a nationally representative statistical distribution of ash composition. As a results, using COALQUAL data to estimate bulk compositions of coal combustion residuals is challenging and does not necessarily result in an improvement over the 2014 dataset.

2.3 Comments on Disposal Unit Groundwater Risk (RA Section 3)

2.3.1 The conclusion that facilities which were not previously modeled may pose "*somewhat higher*" risk is predicated on a visual observation concerning facility locations that is not clear and could be quantified. (Section 3.2)

The 2023 Draft RA states on page 3-4: "*Furthermore, the location of these remaining legacy facilities are concentrated in the eastern half of the country. This will tend to result in facilities more concentrated in regions of higher precipitation than considered nationally. Thus, the modeled risks for these units may be somewhat higher than those previously modeled for the entire country*." Review of Figure 3-1 shows that the legacy facilities are concentrated in the eastern part of the country as stated; however, the units that were modeled are also concentrated in the eastern part of the country. The second sentence in this quote infers that the legacy facilities are more concentrated in the eastern part of the country than the facilities modeled in 2014, and that inference is not apparent in Figure 3-1. A statistical summary of 2014 and legacy facility locations by US region is needed to support the second sentence. In addition, without running a new model to include the facilities that were not previously modeled, the effect of this clustering, on a model with many other inputs, is not known at the 50th or 90th percentiles.

2.3.2 The underlying data for Figure 3-2, showing modeled risk as a function of area and unit mass are not provided in the NODA or supporting documents, and without these data it is not possible to validate the results drawn from this figure.

Figure 3-2 summarizes risks predicted by the 2014 Draft RA modeling as a function of unit area and fill volume. This information is directly relevant to CCRMU evaluation, because EPA reasonably assumes that CCRMU will tend to be smaller than the landfills modeled during the 2014 RA. The curves shown on this figure are a running average, with the number of results in each group determined by "*trial and error*" (Page 3-4). However, the underlying data used to calculate these running averages were not provided, and it is therefore not possible to directly evaluate the effects that the averaging had on the results plotted in Figure 3-2 or on the conclusions drawn from this figure. To gain perspective on this question, EPRI created similar plots using the previously excluded unit data provided with the NODA. Figure 1 is calculated as described for Figure 3-2 in the 2023 Draft RA, and shows a similar risk range for the excluded units as those used in the 2014 RA; although the distributions show in Figure 1 are smoother for mean area (left plot), and both different and smoother for tons/acre (right plot) when compared to Figure 3-2 in the Draft RA. Figure 2 plots the same data, but with a smaller averaging group size of 100. Comparing Figure 1 and Figure 2 shows that the selected group size affects the overall

risk range and that large grouping such as used in Figure 1 of this comment package and Figure 3-2 of the Draft RA can mask both high and low risks.[4]

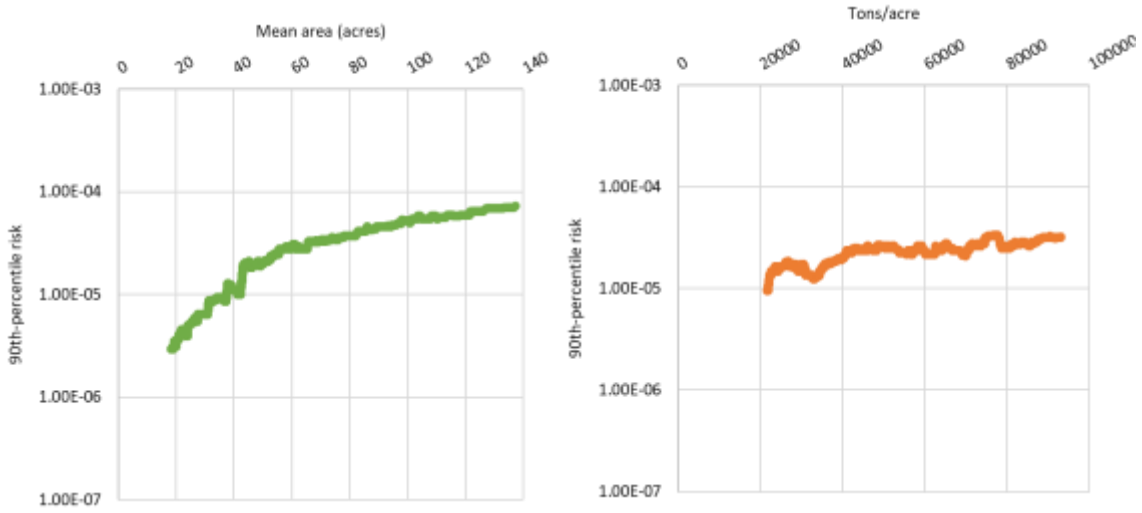


Figure 1. Modeled risks as a function of area and mass per area based on results from previously excluded units and using a running 90th percentile for groups of 2,000 runs.

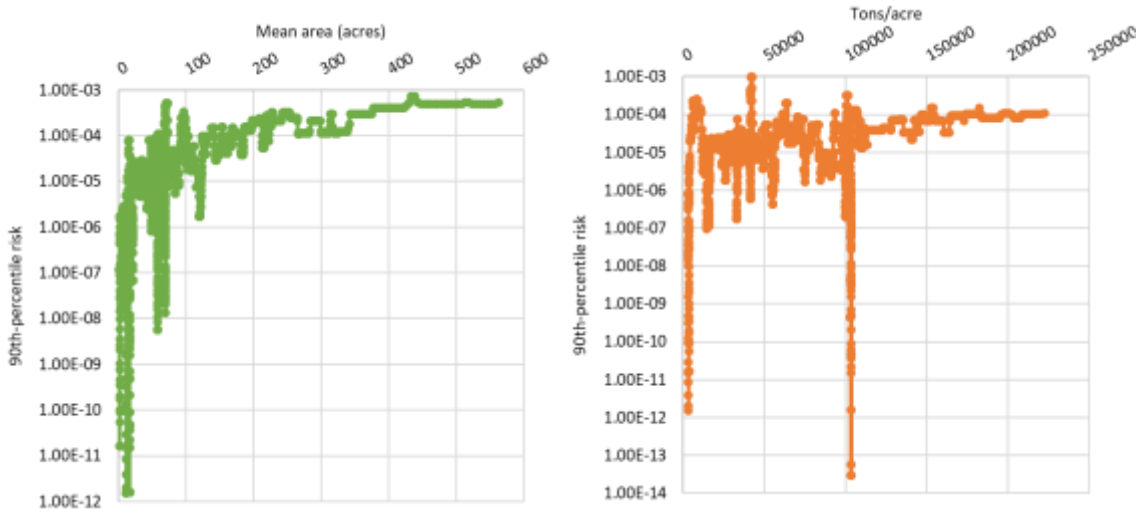


Figure 2. Modeled risks as a function of area and mass per area based on results from previously excluded units and using a running 90th percentile for groups of 100 runs.

On page 3-5 the 2023 RA observes that "*High-end risks fell above the 1×10^{-5} point of departure across the full range of values*" for the tons/acre plot, and that "*modeled landfill risks start to consistently decline only beyond a certain size, falling below the 10^{-5} around 15 acres, but remaining within the risk range*" for the acres plot. However, without the underlying data and observing that the

[4] Note that the X and Y axes both change as group size changes from 2000 to 100. That is because the grouping affects both the risk result (Y axis), and the calculated acreage and tons/acre (X-axis).

running average can mask both high and low risk results, it is not possible to assess the validity of these observations.

2.4 Comments on CCRMU Groundwater Risk (RA Section 4)

2.4.1 The description of calculating bulk composition from COALQUAL data is ambiguous, and forces the reader to make assumptions to review the application. (Section 4.2.4)

The 2023 Draft RA is ambiguous with respect to the estimation of coal ash bulk composition from COALQUAL data. The Draft RA indicated on page 4-3 that "*COALQUAL reports constituent concentrations on a whole coal basis. Therefore, additional steps were required to estimate concentrations in the resulting ash*." The Draft RA then described two values of ash content included in COALQUAL and indicated GSAsh was selected to estimate concentrations in ash. However, the Draft RA never explained how concentrations in ash were calculated, nor were the calculated values provided in appendices. For the purpose of reviewing the Draft RA, EPRI assumed the Draft RA coal combustion product bulk composition was calculated by simply dividing the COALQUAL bulk coal concentration (mg element per kg coal) by the corresponding GSAsh value (kg ash per kg coal reported as percent). Using this approach does not account for unburned carbon in powerplant ash as described in Comment 2.4.2.

2.4.2 The use of GSAsh in calculation of coal ash bulk composition from COALQUAL data is not supported by analysis to confirm it represents powerplant ash values, and overestimates trace element concentrations in powerplant ashes that contain unburned carbon. (Section 4.2.4)

The 2023 Draft RA indicated GSAsh Dry values were selected rather than ASTM ash values in an effort to account for unburned carbon (described by EPA as "*residual volatile matter*") present in powerplant ash. The GSAsh test is not designed to represent powerplant combustion conditions and does not reproduce the unburned carbon in powerplant ash. Unburned carbon in powerplant ash depends on plant design and operations and is also influenced by fuel rank, with lower rank coals exhibiting lower unburned carbon than higher rank coals. Because the GSAsh Dry values do not account for unburned carbon in powerplant operation, bulk compositions calculated using GSAsh Dry values overestimate the concentrations of powerplant ashes, with the degree of overestimation dependent on powerplant and fuel characteristics. The 2023 Draft RA did not provide a comparison with GSAsh Dry and powerplant ash values to support the use of GSAsh Dry values, nor was an assessment of the sensitivity of the Draft RA to the use of GSAsh Dry provided.

2.4.3 The description of COALQUAL data filtering may contain a transcription error. (Section 4.2.4)

The 2023 Draft RA included unfiltered COALQUAL data in Appendix B. Filtered data were not supplied. EPRI was unable to exactly reproduce the filtering based on the description on page 4-4. In particular, EPRI did not find the exact terms used for filtering "Sample Description" in that column. However, EPRI found the exact terms in the adjacent column "Estimated Rank." For its comments, EPRI assumed this was a transcription error and filtered the COALQUAL data by

removing samples that contain "bone," "shale," "clay," "pyrite zone," "coal," or "carbonaceous to coaly shale" in Estimated Rank.

2.4.4 The COALQUAL filtering substantially reduced the number of western coal samples in the Draft RA and the validity of the filtering criteria to represent commercial coals was not evaluated. (Section 4.2.4)

The 2023 Draft RA noted unfiltered COALQUAL data contained "*nearly 7,500 samples of coal"* (Page 2-9). The filtering by Mine/Powerplant and Estimated Rank reduced the number of samples to about 3,100 to 3,600 depending on trace element of concern. However, the quantitative result of the filtering on the number of western coals or number of subbituminous coals in the dataset was not described. Filtering Mine/Powerplant and Estimated Rank reduced the number of western coals in the dataset from about 2600 samples to 460 samples, and the number of subbituminous samples from about 1240 to 130. That is, the draft RA approach to filtering substantially reduced the number of western and subbituminous samples in the dataset.

Due to time and data constraints, EPRI was unable to fully evaluate the ability of the filtering approach to represent powerplant coal. However, EPRI notes that the filtered COALQUAL data set includes only 5, 5, and 9 samples from the top ten US coal producing mines in 2022, 2002, and 1983, respectively. The top ten coal mine production data and filtered sample representation are summarized in Table 1.

Furthermore, the Draft RA includes only 67 samples from Wyoming, the top coal producing state. Based on arsenic, trace element concentrations for ash calculated from the 67 coal samples in the Draft RA are not representative of trace element concentrations in ash from commercial Wyoming coal in the 2009 Utility MACT ICR (EPA 2011a and 2011b; Table 2). Only four of the 67 records are for coal from Campbell County, which was responsible for 90% of Wyoming coal production (and 39% of total US production) during 2009 (Table 3). This lack of samples from Campbell County relative to production likely explains the bias in Wyoming COALQUAL arsenic in comparison to ICR data.

Table 1. Summary of EIA Coal Mine Production Data and Number of Named Samples in COALQUAL.

2022 Domestic Coal Production (EIA-7A)				**2002 Domestic Coal Production (EIA-7A)**				**1983 Domestic Coal Production (EIA-7A)**			
Mine Name	Tons Coal Produced (million tons)	Percent of Domestic Production	Named Samples in COALQUAL	Mine Name	Tons Coal Produced (million tons)	Tons Coal Produced (million tons)	Named Samples in COALQUAL	Mine Name	Tons Coal Produced (million tons)	Tons Coal Produced (million tons)	Named Samples in COALQUAL
Black Thunder	62	10%	2	North Antelope Rochelle Comple	75	7%	0	Black Thunder Surface Mine	15	2%	2
North Antelope Rochelle Mine	60	10%	0	Black Thunder	65	6%	2	Belle Ayr	14	2%	1
Antelope Coal Mine	22	4%	2	Cordero Mine	38	3%	0	Jacobs Ranch Mine	12	2%	0
Buckskin Mine	18	3%	0	Jacobs Ranch Mine	32	3%	0	Martin Lake Strip	12	1%	0
Eagle Butte Mine	15	3%	0	Antelope Coal Mine	27	2%	2	Eagle Butte	11	1%	0
Belle Ayr Mine	14	2%	1	Caballo Mine	26	2%	0	Cordero	10	1%	0
Freedom Mine	13	2%	0	Eagle Butte Mine	25	2%	0	Rosebud #6	10	1%	4*

Table 1 (continued). Summary of EIA Coal Mine Production Data and Number of Named Samples in COALQUAL.

2022 Domestic Coal Production (EIA-7A)				2002 Domestic Coal Production (EIA-7A)				1983 Domestic Coal Production (EIA-7A)			
Mine Name	Tons Coal Produced (million tons)	Percent of Domestic Production	Named Samples in COALQUAL	Mine Name	Tons Coal Produced (million tons)	Tons Coal Produced (million tons)	Named Samples in COALQUAL	Mine Name	Tons Coal Produced (million tons)	Tons Coal Produced (million tons)	Named Samples in COALQUAL
Cordero Rojo Mine	12	2%	0	North Rochelle	24	2%	0	Monticello Strip	9	1%	0
Caballo Mine	12	2%	0	Buckskin Mine	18	2%	0	Navajo	9	1%	2**
Bailey Mine	12	2%	0	Belle Ayr Mine	17	2%	1	Rawhide Strip	9	1%	0
Top 10 Mines	241	41%	5	Top 10 Mines	347	32%	5	Top 10 Mines	110	14%	9
* All COALQUAL Mine/Powerplants with “Rosebud” are included in this total. ** All COALQUAL Mine/Powerplants with “Navajo” are included in this total											

Table 2. Higher arsenic in coal ash (mg/kg) values are indicated within filtered Wyoming COALQUAL data than by the ICR year 2009 data.

Data Set	Data records	Distribution Statistics									
		min	5th	10th	25th	50th	avg.	75th	90th	95th	99th
Filtered COALQUAL	67	7	11	14	19	26	30	39	49	54	73
ICR 2009	307	2	6	8	11	15	17	21	26	29	74

Note. The arsenic concentrations in ash were simply calculated using GSAsh, and do not account for unburned carbon in powerplant ash. The ICR 2009 data included 424 samples with arsenic assays for Wyoming coal. However, 28% (119) of these assays were flagged as below detection level and these values were not included. Consequently, the distribution statistics for the remaining 307 ICR data records in this table should be considered maximum values.

Table 3. Wyoming coal records in COALQUAL and 2009 ICR by county.

County	All COALQUAL records	Filtered COALQUAL records in Draft RA	Year 2009 ICR records	Coal, million tons in 2009 (EIA)
ALBANY	10			0
CAMPBELL	201	4	242	380
CARBON	125	23		< 1
CONVERSE	14	7	1	31
FREMONT	38			0
JOHNSON	16			0
LINCOLN	17	13		2
SHERIDAN	73	9		0
SWEETWATER	94	11	11	10
TETON	30			0
UINTA	12			0
Not Reported			45	

The validity of using the Mine/Powerplant Field to exclude non-commercial coals was not evaluated in the Draft RA. Furthermore, the Draft RA approach to filtering and its ability to represent commercial coals was not tested using other coal composition data, like data collected in the 2009 Utility MACT ICR. EPRI's limited review of available data indicates commercial western coals are underrepresented in the COALQUAL data, and this underrepresentation resulted in bias within the distribution of arsenic concentrations in Wyoming coal derived ash relative to the ICR distribution.

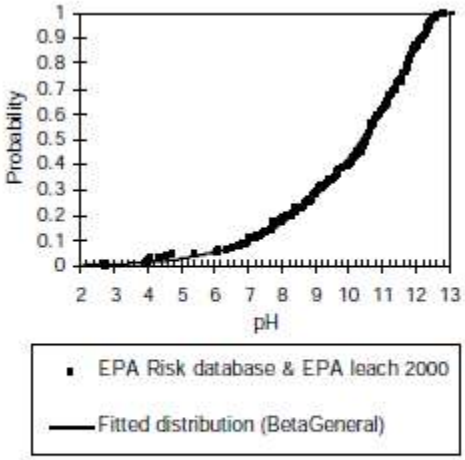
2.4.5 Sampling of filtered COALQUAL data increased reliance on limited western and subbituminous coal data. (Section 4.2.4)

The 2023 Draft RA indicted "*Not all coal in the United States is mined in equal volumes. Therefore, EPA randomly sampled the filtered COALQUAL database a total of 150,000 times in rough proportion to recent production statistics. EPA sampled coal from eastern and western states at a relative proportion of 40:60, respectively (EIA, 2022a). EPA also sampled the different coal types in a relative proportion of 55:45 sub-bituminous to all other types (EIA, 2022b). Because anthracite and lignite represent a very small portion of the database, samples of "all other" types are predominantly bituminous coal*." (Page 4-4)

This simple approach to sampling helps to address the overall bias of COALQUAL towards eastern bituminous coals. However, the distribution of bulk compositions after sampling is still biased by disproportionate representation of small production mines within the database. As noted in Comment 2.4.4, the filtering criteria substantially reduced the number of western and subbituminous samples in the dataset. The Draft RA sampling process weights western and subbituminous samples more heavily. This sampling increases the importance of a relatively small number of samples, and increases the impact of any bias in the western or subbituminous data.

2.4.6 pH values in Figure 4-1 are not representative of field measured pH values for CCR porewater. This observation combined with the observation in Comments 2.4.7 and 2.4.8 makes the model predictions uncertain. (Section 4.2.5)

The pH distribution used by the 2023 Draft RA and shown in Figure 4-1 of the Draft RA is inconsistent with other pH distributions generated for coal fly ash. In particular, this distribution is bimodal, with peaks between pH 3.9 and 5.1 and between pH 11.5 and 12.3. Previous data published by EPA (2009) shows a distribution where the median pH is 10.5 and fewer than 5% of the samples have pH of 5.4 or less (Figure 3). EPRI (2016) compiled pH results from 150 CCR landfills and developed a distribution with a median at pH 7.8, and few results lower than pH 6 (Figure 4). The EPRI data represented in Figure 4 are for all types of CCR in landfills. Figure 5 shows the data ranges from Figure 4 grouped by CCR type and landfill status. Figure 5 shows that the different categories of coal fly ash have an overall pH range similar to the range displayed by EPA (2009), and that ranges for individual categories are dependent on the coal source, with bituminous sources yielding an ash with circumneutral median pH and subbituminous coal sources yielding alkaline pH.



pH	Field data	Fitted distribution	Simulated
Min	2.75	-7.42	2.76
5th percentile	5.40	5.84	5.85
50th percentile	10.53	10.38	10.24
90th percentile	12.20	12.18	11.94
95th percentile	12.40	12.43	12.43
Max	12.80	12.81	12.43

Distributions
BetaGeneral(9.0369, 1.5076, -7.4214, 12.814)

Figure 8. Probability distributions for field pH. Summary statistics for the field data and the probability distribution are provided to the right of the graph (EPA, 2000; EPA, 2007b; EPRI, 2006).

Figure 3. pH probability compiled by EPA 2009, showing a median value of 10.5 and few values lower than pH 5.4. (Figure 8 is the figure number from EPA 2009)

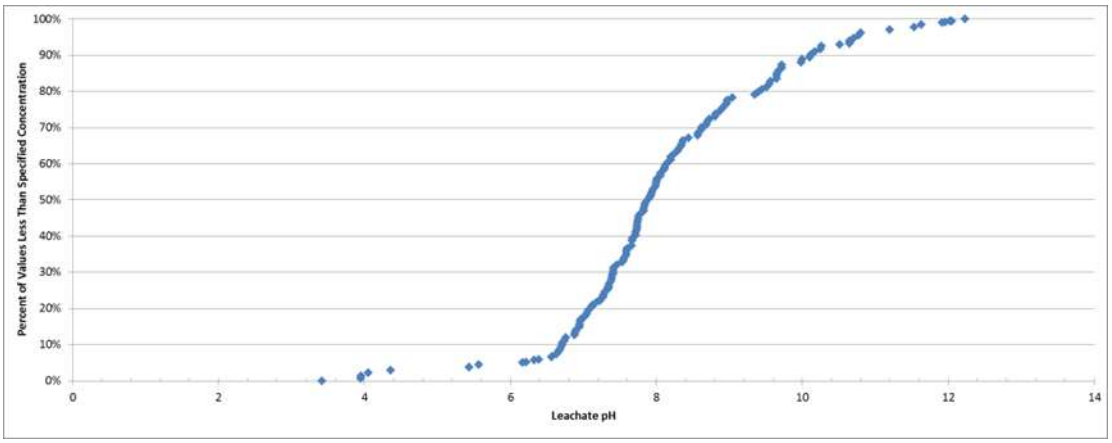


Figure 4. pH probability distribution based on samples from 150 CCR landfills (EPRI, 2016), showing a similar overall range to EPA (2009) with few values lower than pH 6; although with a lower median pH than EPA (2009).

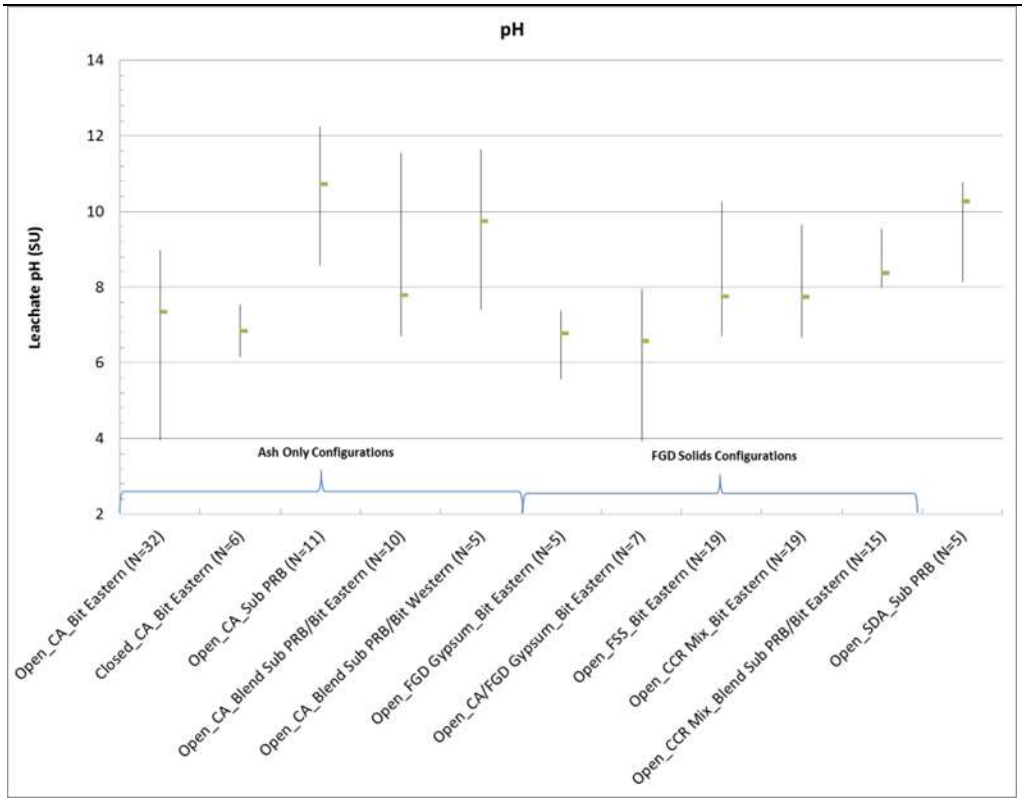


Figure 5. pH ranges categorized by type of CCR and landfill status, using the same data as Figure 4 (EPRI, 2016).

The pH values used in the Draft RA influence the leachate concentrations selected from the LEAF Method 1313 dataset. EPA (2009) showed that Tl concentrations in the pH-dependent leach testing were higher, often by orders of magnitude, at low pH than at alkaline pH for all coal sources; Mo concentrations tended to be lowest at acidic pH for bituminous coal sources, and lowest at both acidic and alkaline pH for subbituminous and lignite coal sources; As was more variable due to other influences, although concentrations varied by an order of magnitude or more based on the pH of the test (see Figures 38 through 41 in EPA 2009). Given this correlation between the method 1313 test concentration and the concentration of As, Mo, and Tl in the eluates from the test, a representative pH is needed for the risk model to yield the most representative result produced by the test. However, as explained in the next comment, the most representative result from the method 1313 test is often not representative of field-measured porewater concentrations.

2.4.7 EPRI research has identified challenges using LEAF methods to predict porewater concentrations. Since EPA has a large field porewater dataset to draw from, and the 2023 Draft RA uses the field dataset for lithium, the modeling process would be more consistent, and results less uncertain, if the field porewater dataset was used for all modeled constituents. (Sections 2.3.4 and 4.2.5)

The 2023 Draft RA used laboratory leaching data generated using EPA method 1313 (LEAF pH-dependent test) to characterize leachate concentrations for As, Mo, and Tl in CCRMU fills, and used field measured porewater results to characterize leachate concentrations for Li (Page 4-6).

EPRI has performed detailed research comparing laboratory leach test concentrations to field-measured porewater concentrations (EPRI 2020, 2021). For this research, the laboratory leach tests were performed on solid samples extracted from the same depths as the screened intervals of the boreholes that the porewater access points (PAPs) were installed in. The comparison was performed for three sample points at one site (EPRI, 2020) and four sample points at another site (EPRI, 2021). Laboratory leach testing was performed on the solid samples using methods 1311 (TCLP), 1312 (SPLP), ASTM D3987 (shake extraction of solid waste with water), 1313 (LEAF pH dependance), and 1314 (LEAF L/S dependance). The laboratory data were then compared to between 8 to 12 field porewater samples collected in the year following PAP installation.

The results of this comparison for As, Mo, and Tl are summarized in Table 4. This summary shows that the 1313 test usually did not yield a concentration within 25% of the mean field-measured porewater concentration. Furthermore, the results were not consistent between sample points.

Given the uncertainty introduced by using the method 1313 data, the uncertainty introduced by the pH distribution used for the 2023 Draft RA (see Comment 2.4.6), and the observation that the 2023 Draft RA is already using field porewater for Li, it would be more consistent for the 2023 RA model to use field porewater measurements as starting leachate concentrations for all elements.

Table 4. Comparison of LEAF Method 1313 laboratory leach test eluant concentrations to field measured CCR porewater concentrations.

	EPRI, 2020			EPRI, 2021			
	VB-1	VB-2	VB-3	VC-1	VC-2	VC-3	VC-4
As	C	B	B	B	B	B	A
Mo	A	C	C	C	C	C	C
Tl	B	A	B	B	B	B	B

Notes:

- A (green shade) = Method 1313 result within 25% of mean field measured porewater concentration
- B (yellow shade) = Method 1313 result not within 25%, but within 1 order of magnitude of mean field measured porewater concentration
- C (red shade) = Method 1313 result not within 1 order of magnitude of mean field-measured porewater concentration
- Based on LEAF Method 1313 at L/S=10 (i.e., unmodified 1313 method)
- See Tables 4-14, 4-15, and 4-16 in EPRI 2020 for other elements and leach test methods

2.4.8 The leachate concentrations simulated for CCRMU in the 2023 Draft RA appear to be anomalously high for As, Mo, and Tl when compared to leachate concentrations measured in the field at CCR landfills, and as a result the risk for these constituents at CCRMU may be overstated. (Section 4.2.5)

EPRI extracted initial leachate concentrations used in the risk model from the EPACMTP input files, and calculated the median and 90th percentile leachate concentrations modeled for CCRMU. These results were then compared to a survey of landfill leachate concentrations assembled by EPRI (2016). The EPRI (2016) data represent average concentrations for individual coal ash units, which is appropriate for comparison to the RA model inputs which are also for individual units. The number of coal ash landfill units represented in the EPRI data is 64 for arsenic, 5 for Li, 56 for Mo, and 31 for Tl.[5] Excluding Li due to the low number of sites in EPRI (2016), the following observations can be made for As, Mo, and Tl based on this comparison:

- The As median from the CCRMU RA modeling is similar to the median concentrations compiled by EPRI, but the 90th percentile is a factor of 3 to 4 higher than the highest value for any of the EPRI (2016) sites (Figure 6).

- The Mo median from the CCRMU RA modeling is at the high end of the medians compiled by EPRI (2016), and the 90th percentile is a factor of 2 to 3 higher than the highest value for any of the EPRI (2016) sites (Figure 7).

- The Tl median and 90th percentiles from the CCRMU modeling are higher than the highest value for any of the EPRI (2016) sites. The RA median input value is a factor of 7 higher than the highest median in the EPRI data and the 90th percentile value is more than an order of magnitude higher than the highest value for any of the EPRI (2016) sites (Figure 8).

This comparison, combined with the observations in comments 2.4.6 and 2.4.7, indicate that the input concentrations used in the 2023 Draft RA model for CCRMU risk are biased high by the methods used to generate these model inputs. Leachate concentrations input to analytical models directly affect predicted concentrations and resulting risk values, and the highest concentrations will drive 90th percentile risk results. These observations suggest that the high-end risks presented in the 2023 Draft RA may be overstated for As, Mo, and Tl, and the median risk for Tl may also be overstated. No assessment can be made for Li (Figure 9) due the small number of landfills with field leachate in EPRI (2016).

[5] The EPRI (2016) dataset includes landfill field leachate data from three sources: 1) prior EPRI research; 2) reported by power companies for the 2016 survey; and 3) samples collected as part of the mandated EPA ELG Information Collection Request (ICR) from 2009/2010.

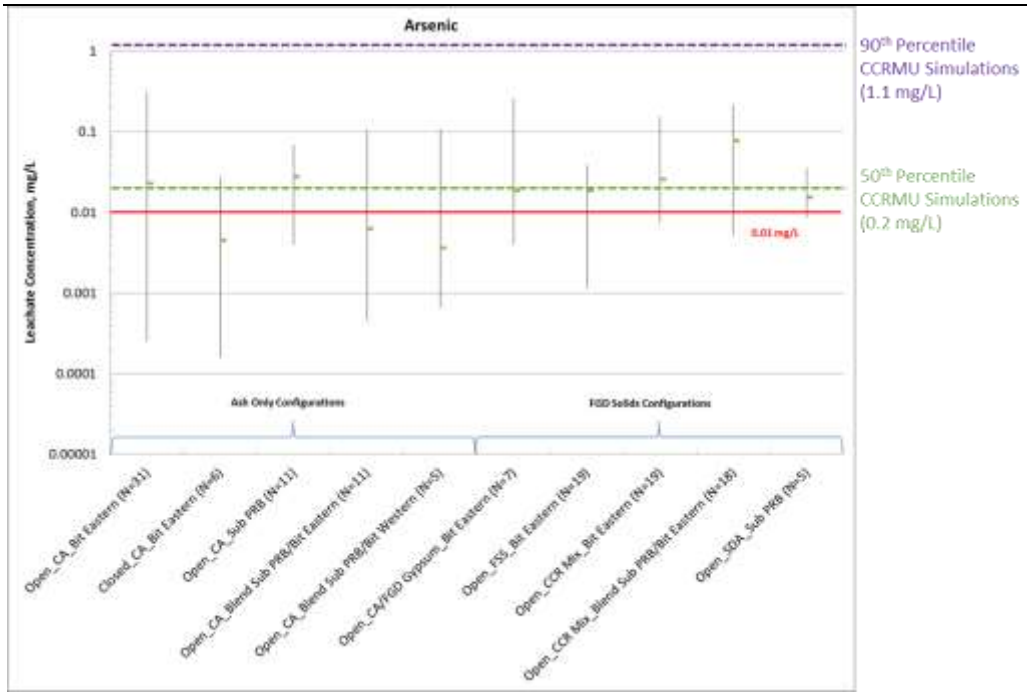


Figure 6. Comparison of 50th percentile (median) and 90th percentile arsenic concentrations from the CCRMU RA model to field leachate data for landfills reported in EPRI (2016).

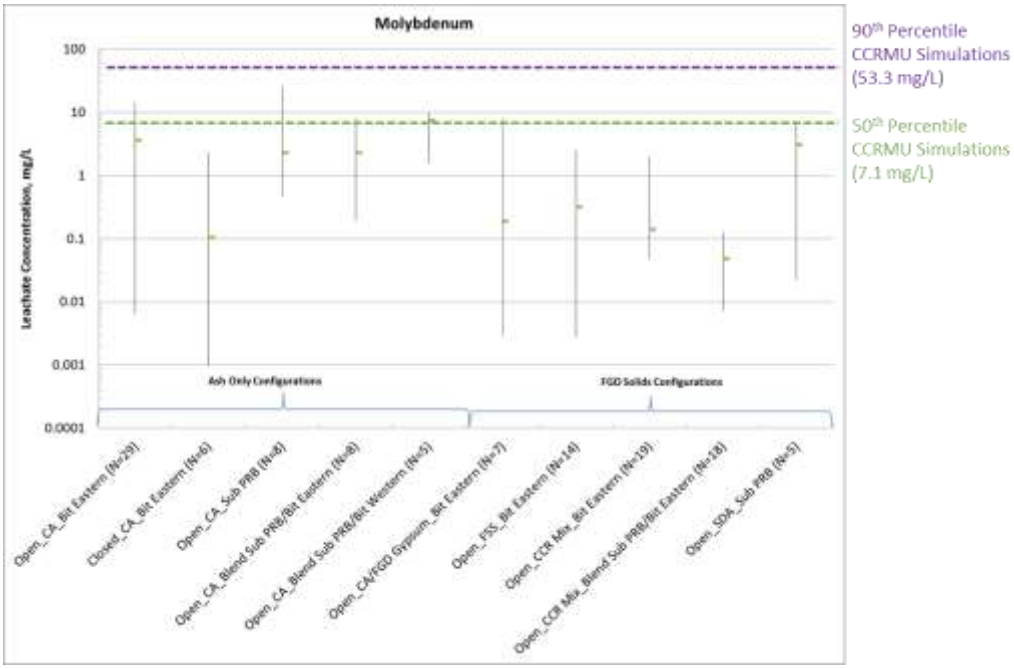


Figure 7. Comparison of 50th percentile (median) and 90th percentile molybdenum concentrations from the CCRMU RA model to field leachate data for landfills reported in EPRI (2016).

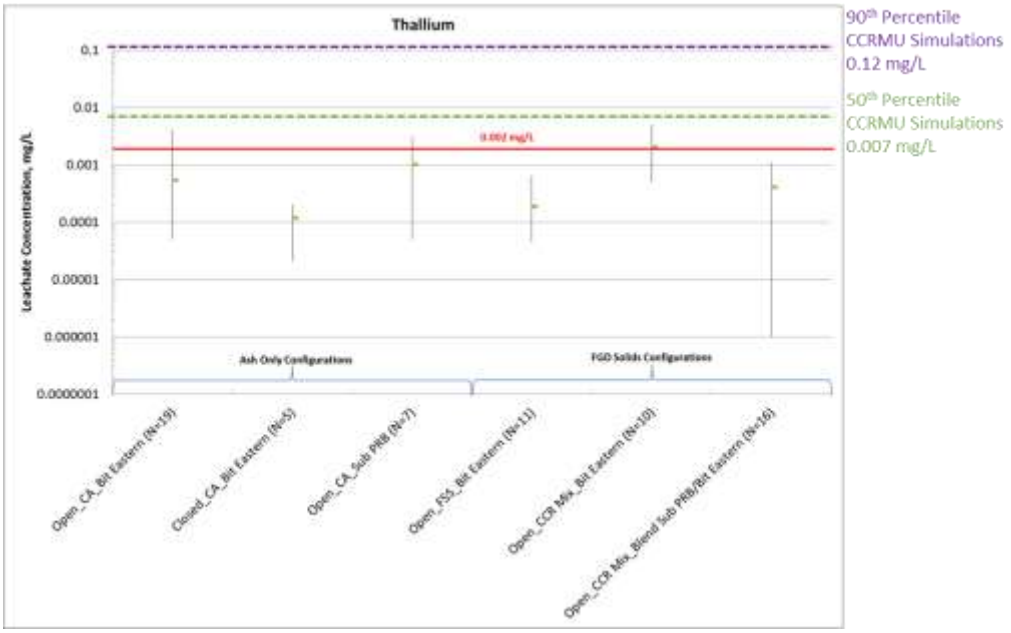


Figure 8. Comparison of 50th percentile (median) and 90th percentile thallium concentrations from the CCRMU RA model to field leachate data for landfills reported in EPRI (2016).

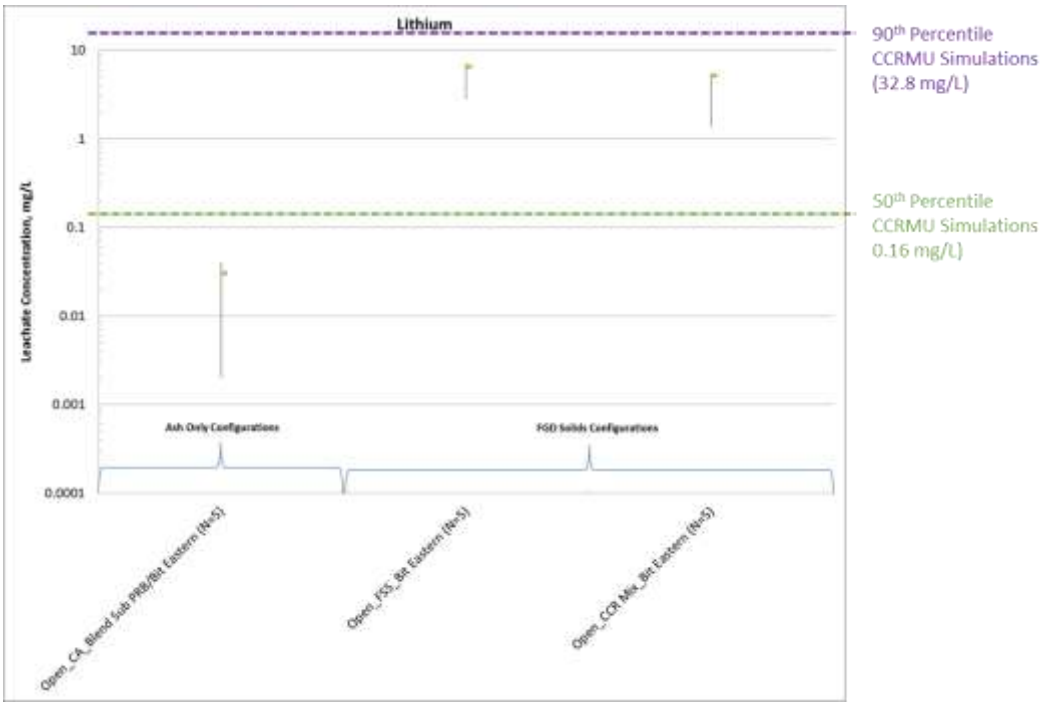


Figure 9. Comparison of 50th percentile (median) and 90th percentile lithium concentrations from the CCRMU RA model to the limited field leachate for landfills data reported in EPRI (2016).

2.4.9 The 2023 Draft RA model takes a more conservative approach to selecting the sampling locations and depths where model results are tabulated than the 2014 RA by narrowing the range of locations and depths and excluding effects of plume interception by surface water. No information is provided for the readers to understand how these differences from the 2014 RA affect predicted concentrations and resulting risk conclusions. (Section 4.2.8)

The 2023 model specifies the sampling location at fixed distances of 10, 100, and 1000 feet along the centerline of the fill boundary, while the 2014 RA model randomly selected a distance within a range of less than 100 feet to a mile or more from the CCR unit[6] and did not limit position to be along the centerline of the plume. One input to analytical models that affects predicted concentration is longitudinal dispersion (dispersion in the direction of plume migration that reduces maximum concentration predicted by an analytical model). This effect is dependent on factors such as the distance from the source, the retardation simulated by the model, and the duration that the release was simulated relative to total simulation time. No information was provided to inform readers how this change from the randomly selected distance approach in 2014 to a fixed distance approach in 2023 affected predicted concentrations or resulting risk.

Another input to analytical models that affects predicted concentration is transverse dispersion (dispersion laterally from the direction of plume migration that decreases concentration predicted with an analytical model). If all other factors are the same, then limiting sampling location to the centerline of the plume can result in less concentration reduction via transverse dispersion than for a location off the centerline. This effect is dependent on other factors such as the distance off-center relative to sample location and the width of the modeled source. No information was provided to inform readers how limiting sampling location to the centerline of the plume for the 2023 model affected predicted concentrations and resulting risk compared to the 2014 approach of enabling locations to be off the centerline of the plume.

The 2023 model also limits the sampling depth to between 0 and 5 feet of the top of the aquifer. Conversely, the 2014 RA randomly selected a depth between 0 and the lesser of the full thickness of the aquifer or 10 m (~30 feet). The analytical model calculates the highest concentration at a depth of 0 feet, and concentration can then decrease with depth as a function of vertical dispersion. This effect is dependent on other factors such as the depth from the top of the aquifer relative to the distance from the modeled source. No information was provided to inform readers how limiting sample depths to the upper 5 feet of the aquifer for the 2023 model affected predicted concentrations and resulting risk compared to the 2014 approach of enabling depths as much as ~30 feet below the top of the aquifer.

Finally, the 2023 model does not include plume interception by surface water in their modeling for CCRMU fills, while the 2014 model did consider this effect. The presence of surface water can affect predicted concentrations and risk, as noted by EPA in the 2014 RA: "*Median risks for both surface impoundments and landfills were substantially lower than both the high-end risks in this risk assessment and the median risks modeled in the 2010 Risk Assessment (U.S. EPA,*

[6] The range of possible distances was not specified in EPA (2014) and EPRI does not have access to 2014 RA results to view calculated distances, so the maximum distance is unknown to EPRI. However, review of the input data for the excluded units presented in this NODA identified receptor distances ranging from 20 meters to more than 2000 meters for landfills.

2010a). This decrease is attributed primarily to the interception of ground water by surface water bodies, which is accounted for in the revised risk assessment to provide a more accurate mass balance of constituent mass during transport. It is common for coal-fired utilities to be located near water bodies, which are used as a source of cooling water and conveyance of waste. As a result, in the majority of model iterations, the interception of ground water by surface water bodies resulted in negligible downstream well concentrations" (EPA, 2014, p. ES-5). Furthermore, EPA previously estimated that 67% of groundwater plumes from CCR sites would be intercepted by a surface water body prior to reaching a receptor well (EPA, 2010, p. 119). Ignoring surface water interception rejects EPA's prior conceptual site model.

2.4.10 The modeling conducted for the 2023 Draft RA uses the single-value K_d approach for arsenic adsorption, which ignores the geochemical sensitivity of arsenic to variable groundwater conditions and does not meet current standards of practice. (Section 4.3, Table 4-2)

The 2023 Draft RA provided the K_d (distribution coefficient) values for As^{3+} and As^{5+} used for the unsaturated zone and saturated zone for each simulation, which had a broad range. In some saturated zone scenarios, the K_d values varied by as much as 8 orders of magnitude between As^{3+} and As^{5+} (model scenario MC #40966) or as little as 1.44E-7 m^3/gram (MC #57999). Likewise, in many scenarios the K_d values differed between the saturated and unsaturated zones, but in other scenarios, the K_d values were nearly identical across the zones (MC #62797). The rationale for these selections were not provided.

In groundwater, arsenic can be present in two valence states, as arsenite species [As^{3+}], and as arsenate species [As^{5+}] (Hem, 1992). At a pH of up to around 9, arsenate shows maximum affinity for adsorption of metal (hydr)oxides (highlighted in green on Figure 10; Goldberg, 2002; Smith, 1999). Arsenite has a lower affinity for sorption than arsenate and is generally regarded to be more mobile in natural environments (Nordstrom et al., 2014; Smith, 1999). At low pH (<5), arsenic is more apt to being mobile in groundwater when metal adsorption surfaces are dissolved (Nordstrom et al., 2014). The sorption of arsenic under varying pH and redox conditions onto ferrihydrite (Dzombak and Morel, 1990; Schwertmann, 1988), manganese oxides (Tonkin et al., 2004), and gibbsite (Karamalidis and Dzombak, 2011) has been well studied, as well as arsenic adsorption onto clay minerals (Manning and Goldberg, 1996). Arsenic precipitation as sulfide minerals (AsS, As_2S_3, and FeAsS) is also a well-established method of attenuation (Nordstrom et al., 2014). Thus, attenuation of arsenic in the subsurface is generally well understood.

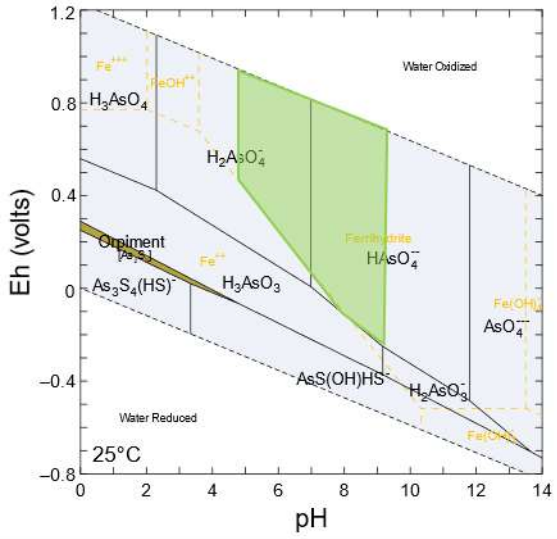


Figure 10. Arsenic Pourbaix diagram showing ideal attenuation zone in green.

The 2023 Draft RA's use of a single partitioning coefficient across a site for each zone (saturated or unsaturated) ignores the variations in aquifer and groundwater conditions that are integral to governing arsenic transport. Merkel and Planer-Friedrich (2005) clearly stated 20 years ago: "the K_d concept must be rejected in most cases because of its oversimplification and its low suitability for applications to natural systems." They further observe: "…[MODFLOW] can handle a set of constituents, however, only by means of the K_d concept. Therefore, real world problems cannot be modeled by this approach and it [MODFLOW] is not a reactive transport code." Bethke and Brady (2000) also note that "The results of K_d-based models have proven in case after case to be inconsistent with laboratory and field observations." Further, EPA's 2004 study of partition coefficient values specifically stated in the arsenic chapter that readers may want to consider using geochemical models and that arsenic adsorption was extremely variable even across a small range of pH (EPA, 2004).

EPA (2004) also reported a range of K_d values. These values were from multiple sources and generally, depending on site type and soil classification, the K_d values ranged from 0.19 to 6.46 mL/gram (Mariner et al., 1996) at a Superfund site, 1.9 to 18 mL/gram for agricultural soils and 1 to 10 mL/gram for the Savannah River Site. Strenge and Peterson (1989) list a K_d for arsenic of 5.86 and 19.4 mL/gram at a pH range of 5 to 9, for <10% and >10% clay, organic matter, and metal hydroxides, respectively. However, based on a review of the K_d values used by the 2023 Draft RA, K_d values modeled for the RA were orders of magnitude lower than these published values and in most cases, below their own recommended ranges. In multiple scenarios (MC#s 26188, 2202, 27190, 55265, 57959, 62618), low K_d values for As^{5+} (0.46 mL/gram) and even lower for As^{3+} (3.99E-7 mL/gram) were used in transport simulations, which limits attenuation and retardation while maximizing the risk associated with arsenic mobility.

The development of an attenuation model using surface complexation that takes into account changes in groundwater pH, redox, arsenic speciation, aquifer heterogeneity, and adsorption site

density is needed for representative arsenic transport results. The modeling conducted for the 2023 Draft RA does not meet this standard of practice given the use of the single-value K_d approach, which ignores the geochemical sensitivity of arsenic to variable groundwater conditions.

2.4.11 The 2023 Draft RA approach to MODFLOW modeling is constrained relative to the capabilities of the models used. Additional and more refined modeling can be performed using the same modeling approaches as described in the Draft RA. (Section 4.3)

- The MODFLOW approach unnecessarily uses specific yield parameters, stating on Page 4-12 that "*MODFLOW simulates transient flow and so required an additional input parameter*." However, MODFLOW can be run to simulate steady-state flow.

- The MODFLOW approach for the 2023 Draft RA uses the unstructured grid form of MODFLOW (2013), but then assigns a rectilinear grid that could have been implemented in the more common and current MODFLOW 6 routine, initially released in 2017 and updated regularly into 2023.

2.4.12 The 2023 Draft RA did not provide sufficient data to evaluate the MODFLOW modeling. (Section 4.3)

- Domain size, boundary conditions, and other modeling parameters are not provided, and the Draft RA does not document or present the model consistent with USGS MODFLOW model archiving standards (see, e.g., https://water.usgs.gov/ogw/policy/gw-model/).

- Page 4-13 (Section 4.3.2) states that "*EPA specified a boundary condition equal to the leachate concentration to serve as the contaminant source*." No information is provided to inform the reader if the leachate concentration specified at this boundary depletes over time.

- The 2023 Draft RA does not state how mass leaves the model domain, and therefore provides insufficient information to verify mass balance.

- The 2023 Draft RA does not describe what contaminant transport package was used. This information is useful for reviewers and commonly provided in modeling reports.

- An order of magnitude mismatch is shown between EPACMTP and MODFLOW inputs on length of pile or fill in the direction of groundwater flow (Appendix C-3). No information is provided to inform how this difference affects model predictions.

2.5 Comments on CCRMU Fill Soil Risks (RA Section 5)

2.5.1 The assumption of a receptor living directly on top of a coal ash deposit is conservative. (Section 5.4)

On Page 5-11 the 2023 Draft RA provides a risk estimate for a receptor living on top of a CCRMU fill. This is a conservative assumption because it discounts all the mechanisms that would limit such exposure:

- Many coal-fired power plant properties that are planned for decommissioning will be repowered for other power generation activities (gas, solar, batteries, etc.) to take advantage of grid interconnection, available land, and existing NPDES and other permits to increase the speed and decrease the cost of converting to low or no-carbon generation resources. While the industry often did not repower prior to 2015 (the year EPA used as the cutoff), the need to transition to low-carbon and no-carbon energy resources has resulted in a worldwide shift in assessment of assets available at coal-fired power plants slated for retirement.

- Prior to sale of these properties, owners usually perform due diligence as part of the decommissioning process to identify potential environmental liabilities. These investigations will identify the location of CCRMUs, which will be managed during decommissioning. In addition, many buyers will request Phase I/II environmental site investigations, which will identify the risks of building on top of a coal ash deposit, leading to avoidance or mitigation.

- There is documentation available showing that owners of properties with coal ash fills will take their own steps to mitigation contamination issues of all types prior to releasing the property (EPRI, 2012). This limited documentation does not provide evidence that such actions will be taken at all properties, but it does provide evidence that action has historically been taken in the past, and in this case before promulgation of the CCR Rule.

- In cases where there is the potential for CCMUs to remain following owner and buyer due diligence, environmental liens or covenants can be used to mitigate risk. The use of covenants or liens can stipulate that radon gas detectors be installed in indoor spaces, prohibit withdrawal of groundwater, and limit the depth of soil-disturbing activities.

2.6 Comments on Uncertainty and Sensitivity Analysis (RA Section 6)

2.6.1 Radiological data are presented in terms of mg/kg, but the appropriate unit is pCi/g. (Section 6.1)

Tables 6-1 and 6-2 both express radiological concentrations in units of mg/kg; however, the values listed are actually in pCi/g.

2.6.2 The effects of mining practices on calculation of bulk composition of coal combustion residuals from COALQUAL data were not considered. (Section 6.1.1)

As indicated in the 2023 Draft RA, the COALQUAL data represents the entire coal bed. However, mining companies must deliver coal that meets commercial specifications including limits on heating value, ash content, and sulfur content. Therefore, mining companies may not deliver the entirety of the bed to the coal consumer if inclusion of a portion of the bed will drive the fuel out of specification. Selective mining, where portions of the coal bed are not delivered to the consumer, is used by miners to control coal quality, including ash content and characteristics related to environmental performance such as mercury content (Kolker 2014). Because selective mining can avoid pyrite- or clay-rich portions of the coal bed, it may reduce the trace elements relative to the whole bed values in COALQUAL. EPRI was unable to evaluate the significance of selective mining on COALQUAL calculations due to data and time constraints. However, EPRI's limited evaluation suggests there may not be sufficient existing data to directly evaluate the impact of selective mining on trace elements in powerplant ash.

2.6.3 Broad conclusions regarding the impact of coal processing on bulk content of coal combustion residuals calculated from COALQUAL data are not supported by data or analysis. (Section 6.1.1)

The 2023 Draft RA conclusion that coal washing would have a negligible impact on bulk concentrations calculated from COAQUAL data was based on a mistaken assessment of the relative reduction in arsenic and ash from a 1998 EPRI study. The Draft RA cited specific average values of arsenic and ash reduction in the EPRI study. However, EPRI did not provide average values of arsenic or ash reduction associated with coal processing, only individual site data and ranges were provided. The 1998 EPRI study did not aim to determine the industry-wide average reduction in arsenic or ash, but instead provided information to understand the range of technology performance. Furthermore, the 1998 EPRI research described a wide range of reductions resulting from commercial cleaning plants where "arsenic reduction was found to vary from 20 to 85 percent and mercury reduction from 12 to 78 percent" on a heating value basis. The variability of the processing impacts to arsenic and ash contents of coal in the EPRI study show that averages of arsenic and ash reduction do not support a conclusion regarding the impact of coal processing on the extreme values.

Finally, the 1998 EPRI study does not contain data on coal processing impacts associated with the other trace elements of concern in the Draft RA, that is, lithium, molybdenum, thallium, radium, thorium, or uranium. While some of these constituents are associated with pyrite minerals, like arsenic, others are associated with clay or organic phases in coal, and the impact of processing on non-pyrite associated constituents generally differs from pyrite associated constituents. Although time and resource constraints limited EPRI's review of coal processing literature, EPRI located 2021 research by USGS (Kolker 2021) that includes limited trace element data for raw and processed Illinois Basin coals. A summary of the USGS data in Table 5 shows variable apparent reductions and enrichments in trace element concentration on an ash basis. Therefore, a conclusion of negligible impact based on averages for arsenic and ash reductions is not supported by limited available data for the other constituents of concern. Although EPRI was able to locate this limited data, we do not know if there are sufficient

existing data on coal processing to support broad conclusions regarding impact of coal processing on trace element concentrations in powerplant ash. Additional research may be necessary to evaluate the impact of coal processing if COALQUAL data are to be used for evaluation of coal ash bulk composition.

Table 5. Summary of raw and clean coal trace element ash basis concentrations for Illinois Basin Fuels from USGS (Kolker 2021).

Sequential sample no.	Coal bed	Sample type	Field sample identification	Mo (ppm)	Tl (ppm)	Th (ppm)	U (ppm)	Li (ppm)
1 *	Herrin #6	Raw coal	IL-1	35	11	13	12	35
8 *	Herrin #6	Final product	IL-8	123	7	17	72	85
14	Herrin #6	Raw coal	IL11-SM 1H ash	37	4.2	13	10.4	nr
15	Herrin #6	Clean coal	IL12-SM 2H ash	92	2.4	17.2	22.1	nr
17	Springfield #5	Raw coal	IL14-V 1S ash	21	3.4	10.4	7.7	nr
18	Springfield #5	Clean coal	IL15-V 2S ash	40	4.8	11.7	14.5	nr
20	Herrin #6	Clean coal	IL17-BH 1H ash	29	7.9	11.8	4.7	nr
21	Herrin #6	Raw coal	IL18-BH 1H ash	22	6.3	17.9	8.4	nr
22	Springfield #5	Raw Coal	IL19-BH 1S ash	33	8.2	15.9	8.7	nr
23	Springfield #5	Clean coal	IL20-BH 2S ash	22	4.4	19	9.1	nr
24	Murphysboro	Raw coal	IL21-CP 1M ash	44	4.5	24.5	15.5	nr
25	Murphysboro	Clean coal	IL22-CP 2M ash	20	2.9	25	14.3	nr
26	De Koven	Raw coal	IL23-ER 1D ash	24	15.1	7.8	5.4	nr
27	De Koven	Clean coal	IL24-ER 2D ash	18	6.1	15.5	12	nr
33	Herrin #6	Clean coal	IL30-PM 2H ash	>100	6	15.9	24	nr
35	Herrin #6	Raw coal	IL32-MM 1H ash	17	4.1	13.8	7.2	nr
36	Herrin #6	Clean coal	IL33-MM 2H ash	65	8.1	16.1	17.2	nr
39	Herrin #6	Raw coal	IL36-WH 1H ash	14	3.3	11.6	4.9	nr
40	Herrin #6	Clean coal	IL37-WH 2H ash	>100	6.4	18.3	78.1	nr
42	Herrin #6	Clean coal	IL39-LG 2H ash	42	4.4	13.2	24.6	nr
45	Danville #7	Raw coal	BR-DAN 1-2 ash	15	3.5	16.8	6.1	nr
46	Danville #7	Clean coal	BR-DAN 4 ash	45	5.2	17.8	22.9	nr

* Denotes samples where ash basis values were calculated by EPRI from reported whole coal concentration by dividing by the reported ash content; nr denotes values not reported

2.6.4 The higher infiltration with HELP version 4 versus version 3, depicted in Figure 6-1, does not necessarily indicate that the 2014 risk assessment underestimated risk.

Page 6-9 of the 2023 Draft RA states: "*Higher infiltration into a landfill will result in greater risks because of the greater volume of resulting leakage into groundwater over time. Therefore, EPA believes it is likely the 2014 Risk Assessment underestimated the magnitude of potential leakage and associated risk from CCR landfills after closure*." The information provided leading up to this quote does not support the statement that the 2014 Risk Assessment underestimates risk. First, the data in Figure 6-1, which is used to support this statement, is based on comparative modeling for only one soil type. Without further modeling, it is not possible to determine how representative Figure 6-1 is for all soil types considered for the risk assessment model. Second, infiltration is only one of many inputs to the Risk Assessment model, and no information is provided to demonstrate that this single input had an effect on calculated risk at either the 50^{th} or 90^{th} percentiles.

2.6.5 The risk endpoints for radionuclides and non-radionuclides are different and not additive. (Section 6.2.2 and Figure 6-2)

The text of the 2023 Draft RA indicates that non-radionuclide and radionuclide were added to develop Figure 6-2: "*The benchmarks corresponding to 1×10^{-5} risk are 6.77 mg/kg arsenic, 0.127 pCi/g Th-232, and 0.162 pCi/g U-238. EPA applied these benchmarks to first calculate a cumulative risk associated with undiluted exposure to each individual sample from the COALQUAL database*" (Page 6-10). However, radionuclides and non-radionuclides have different end points and are not additive, and combining these as stated is not appropriate. Instead of a single plot, there should be a separate plot for the radionuclides and a separate plot for arsenic.

2.7 Comments on Conclusions (RA Section 7)

All of the previous comments from 2.2 through 2.6 collectively reflect on the conclusions; however, one statement is identified here for emphasis.

2.7.1 The statement that historical and inactive units would also be expected to have risks even higher than previously modeled is not fully supported by the data provided. (Section 7.1)

Pages 7-1 and 7-2 of the 2023 Draft RA state: "*Data that has since become available indicates a greater proportion of all disposal units are unlined and the rate of infiltration into landfills is higher than previously modeled. As a result, historical and inactive units would also be expected to have risks even higher than previously modeled*." No modeling was performed to show that these conditions, which are a subset of all conditions considered in the risk assessment model, affect risk results at the 50^{th} and 90^{th} percentiles.

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