SANDIA NATIONAL LABORATORIES WASTE ISOLATION PILOT PLANT

ANALYSIS PACKAGE FOR THE SENSITIVITY OF RELEASES TO INPUT PARAMETERS IN THE 2019 COMPLIANCE RECERTIFICATION APPLICATION PERFORMANCE ASSESSMENT (CRA-2019 PA)

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Executive Summary

The Land Withdrawal Act requires that the U.S. Department of Energy (DOE) apply for recertification of the Waste Isolation Pilot Plant (WIPP) every five years following the initial 1999 waste shipment. The 2019 Compliance Recertification Application (CRA-2019) is the fourth WIPP recertification application submitted for approval by the U.S. Environmental Protection Agency. A performance assessment (PA) has been executed by Sandia National Laboratories in support of the DOE submittal of the CRA-2019. Results found in the CRA-2019 PA are compared to those obtained in the 2014 Compliance Recertification Application (CRA-2014) in order to assess repository performance in terms of the current regulatory baseline. This package documents the parameter sensitivity analysis component of the CRA-2019 PA.

Changes incorporated into the CRA-2019 PA include repository planned changes, parameter updates, and refinements to PA implementation. Several changes are incorporated into the CRA-2019 PA relative to the CRA-2014 PA that potentially impact parameter sensitivity analysis results. The analysis plan for the CRA-2019 PA calculations (AP-181) outlines 16 categories of changes since the CRA-2014 PA. The parameter sensitivity analysis investigates relationships between calculated releases and sampled parameters. Because all of the specified changes impact calculated releases, all 16 changes potentially impact the parameter sensitivity analysis. Eight of the 16 changes also impact parameter sampling, the other key component of the parameter sensitivity analysis.

A stepwise linear multiple regression ("sensitivity") analysis was performed to determine the relative importance of the sampled parameters on the calculated releases for the CRA19 analysis of the CRA-2019 PA, with comparisons made to the CRA14 analysis. The sensitivity analysis is used to resolve the question of which sampled parameters contribute most to the variability (uncertainty) observed in the mean releases by vector. The sensitivity of mean releases of each individual release mechanism, as well as total releases, to sampled parameters was analyzed.

The SOLMOD3:SOLVAR parameter is the most dominant parameter contributing to variability in total releases in all three replicates. The increased importance is due to the shifting of the distribution mean to a higher value (thus making it more impactive on DBRs), the increased contribution of DBRs to total releases, and the occurrence of more nonzero DBRs.

The BOREHOLE:TAUFAIL parameter is the second-most dominant parameter for total releases. The BH_SAND:PRMX_LOG parameter has increased in importance in the CRA19 analysis due to the impact on DBRs. The CASTILER:PRESSURE parameter continues to be one of the more important parameters in terms of variability in total releases, due to its impact on DBRs. Among the other parameters for which distributions were new or updated, only the STEEL:CORRMCO2 and GLOBAL:PBRINE parameters showed substantial change in impact from the CRA14 analysis. The updated distribution for the STEEL:CORRMCO2 parameter has led to increased importance in the variability of DBRs, but the correlation with DBRs is negative—increased gas generation rates associated with this parameter lead to decreased DBRs due to the impact of repository pressure to reduce waste area saturations. Finally, the

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GLOBAL:GDEPFAC parameter (a new parameter related to brine radiolysis) does not have substantial impact on the variability of any release mechanism or total releases.

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1.0 INTRODUCTION

The Waste Isolation Pilot Plant (WIPP), located in southeastern New Mexico, has been developed by the U.S. Department of Energy (DOE) for the geologic (deep underground) disposal of transuranic (TRU) waste. Containment of TRU waste at the WIPP is regulated by the U.S. Environmental Protection Agency (EPA) according to the regulations set forth in Title 40 of the Code of Federal Regulations (CFR), Part 191. The DOE demonstrates compliance with the containment requirements according to the Certification Criteria in Title 40 CFR Part 194 by means of performance assessment (PA) calculations performed by Sandia National Laboratories (SNL). WIPP PA calculations estimate the probability and consequence of potential radionuclide releases from the repository to the accessible environment for a regulatory period of 10,000 years after facility closure. The models used in PA are maintained and updated with new information as part of an ongoing process. Improved information regarding important WIPP features, events, and processes typically results in refinements and modifications to PA models and the parameters used in them. Planned changes to the repository and/or the components therein also result in updates to WIPP PA models. WIPP PA models are used to support the repository recertification process that occurs at five-year intervals following the receipt of the first waste shipment at the site in 1999.

PA calculations were included in the 1996 Compliance Certification Application (CCA) (U.S. DOE 1996), and in a subsequent Performance Assessment Verification Test (PAVT) (MacKinnon and Freeze 1997a, 1997b and 1997c). Based in part on the CCA and PAVT PA calculations, the EPA certified that the WIPP met the regulatory containment criteria. The facility was approved for disposal of transuranic waste in May 1998 (U.S. EPA 1998). PA calculations were an integral part of the 2004 Compliance Recertification Application (CRA-2004) (U.S. DOE 2004). During their review of the CRA-2004, the EPA requested an additional PA calculation, referred to as the CRA-2004 Performance Assessment Baseline Calculation (PABC) (Leigh et al. 2005), be conducted with modified assumptions and parameter values (Cotsworth 2005). Following review of the CRA-2004 and the CRA-2004 PABC, the EPA recertified the WIPP in March 2006 (U.S. EPA 2006).

PA calculations were completed for the second WIPP recertification and documented in the 2009 Compliance Recertification Application (CRA-2009). The CRA-2009 PA resulted from continued review of the CRA-2004 PABC, including a number of technical changes and corrections, as well as updates to parameters and improvements to the PA computer codes (Clayton et al. 2008). To incorporate additional information which was received after the CRA-2009 PA was completed, but before the submittal of the CRA-2009, the EPA requested an additional PA calculation, referred to as the 2009 Compliance Recertification Application Performance Assessment Baseline Calculation (PABC-2009) (Clayton et al. 2010), be undertaken which included updated information (Cotsworth 2009). Following the completion and submission of the PABC-2009, the WIPP was recertified in 2010 (U.S. EPA 2010).

PA calculations were completed for the third WIPP recertification and documented in the 2014 Compliance Recertification Application (CRA-2014). Following the completion and submission of the CRA-2014, the WIPP was recertified in 2017 (U.S. EPA 2017).

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The Land Withdrawal Act (U.S. Congress 1992) requires that the DOE apply for WIPP recertification every five years following the initial 1999 waste shipment. The 2019 Compliance Recertification Application (CRA-2019) is the fourth WIPP recertification application submitted by the DOE for EPA approval. The PA executed by SNL in support of the CRA-2019 is detailed in AP-181 (Zeitler 2019a). The CRA-2019 PA includes repository planned changes, parameter updates, and refinements to PA implementation. Results found in the CRA-2019 PA are compared to those obtained in the CRA-2014 in order to assess repository performance in terms of the current regulatory baseline. This analysis package documents the parameter sensitivity analysis component of the CRA-2019 PA analysis.

1.1 Changes Since the CRA-2014

Several changes are incorporated in the CRA-2019 PA relative to the CRA-2014 PA that potentially impact parameter sensitivity analysis results. The analysis plan for the CRA-2019 PA calculations (AP-181) outlines 16 categories of changes since the CRA-2014 PA (Zeitler 2019a). The parameter sensitivity analysis investigates relationships between calculated releases and sampled parameters. Because all of the changes impact calculated releases, all 16 changes potentially impact the parameter sensitivity analysis. Eight of the 16 changes also impact parameter sampling (Zeitler 2019b). The changes are (note: those changes marked with an * also impact parameter sampling):

- Inclusion of an approach to accommodate the operational decisions to not emplace panel closures in Panels 3, 4, 5, and 6 and to not emplace waste in Panel 9.
- Inclusion of an approach to accommodate an additional shaft connecting the repository to the surface, as well as an additional mined region in the repository north end to accommodate drifts that lead to the new shaft.
- *Refinement of the gas generation process model to include brine radiolysis.
- *An update to the probability that a drilling intrusion into a repository excavated region will intersect the Castile brine reservoir modeled in BRAGFLO.
- *Refinement to the corrosion rates of steel under humid and inundated conditions.
- *Refinement to the effective shear strength of WIPP waste.
- *Refinement to colloid enhancement parameters associated with actinide mobilization.
- *Refinement to the hydromagnesite to magnesite conversion rate.
- Removal of two chemical reactions associated with iron sulfidation.
- Correction to the length of the northernmost panel closure representation in the BRAGFLO grid.
- Updates to drilling rate and plugging pattern parameters.
- Updates to WIPP waste inventory parameters.
- *Updates to radionuclide solubilities and their associated uncertainty.

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- An update to the BH_OPEN:RELP_MOD parameter.
- Introduction of new materials to define properties in some disturbed rock zone areas.
- *Hardware and computational code updates.

Changes related to parameter sampling are summarized in Section 1.1.1 below and discussed in detail in Zeitler (2019b). Changes to the repository representation, which indirectly impacts the parameters sensitivity analysis through impact on releases, is summarized in Section 1.1.2 below and discussed in detail in (Zeitler 2019a). The impacts on releases for changes listed above are summarized in Section 1.1.3 below and discussed in detail in Brunell (2019) and its supporting documentation.

1.1.1 Summary of Changes to Sampled Parameters

Changes since the CRA-2014 PA have resulted in the sampling of 64 uncertain parameters by the LHS method for the CRA19 analysis of the CRA-2019 PA (Zeitler 2019b). Most of the distributions used for the CRA19 analysis were identical to those used in the CRA14 analysis. Two parameters were new to LHS sampling analysis for the CRA-2019 PA: GLOBAL:GDEPFAC and STEEL:HUMCORR. Additionally, six other parameters have updated distributions since the CRA14 analysis¹: GLOBAL:PBRINE, STEEL:CORRMCO2, BOREHOLE:TAUFAIL, WAS_AREA:HYMAGCON, SOLMOD3:SOLVAR, and SOLMOD4:SOLVAR (Table 1). The PHUMOX3:PHUMCIM parameter, which was sampled for the CRA-2014 PA, has been replaced by a constant value for the CRA19 analysis. The parameter distribution for the PHUMOX3:PHUMCIM parameter was not shown to be impactful on the variability of releases in the CRA-2014 PA (Kirchner 2013).

¹ In the context of comparisons with the CRA19 analysis in this report, the CRA14 analysis refers to the CRA14 (Rev. 2) analysis performed subsequent to the migration of WIPP PA codes to the Solaris system (Kirchner et al. 2014, Kirchner et al. 2015).

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Table 1 – Parameters Sampled by LHS with New Distributions for the CRA19 Analysis

Material	Property
BOREHOLE	TAUFAIL
GLOBAL	GDEPFAC ^a
GLOBAL	PBRINE
SOLMOD3	SOLVAR
SOLMOD4	SOLVAR
STEEL	CORRMCO2
STEEL	HUMCORR ^a
WAS_AREA	HYMAGCON

^aParameter not sampled in CRA14 analysis

1.1.2 Summary of Changes to Repository Model for the CRA19 Analysis

Changes to the repository representation used by the BRAGFLO code, as well the relationships between panels, have been implemented for the CRA19 analysis and have had substantial impact on its results (Day (2019), Brunell (2019)). As part of the CRA19 analysis defined in the analysis plan for CRA-2019 PA calculations (Zeitler 2019a), some changes were made to the repository model that were initiated in reponse to operational changes at the WIPP, including the abandonment of run-of-mine panel closures in Panels 3, 4, 5, and 6 and abandonment of waste emplacement in the area designated as Panel 9. These changes were first implemented in the APCS analysis, which was performed subsequent to the CRA14 analysis (Zeitler et al. 2017), and then carried forward for the CRA19 analysis based on a common understanding between the DOE and EPA that this approach is appropriate for handling the operational changes from a PA perspective (Zeitler 2019a).

In the BRAGFLO grid, the southernmost panel closure area (between the waste panel (WP) and south rest-of-repository (SROR)) was effectively removed as a barrier by assigning looser "open area" parameters. In the DBR grid, panel closure areas for Panels 3, 4, 5, and 6 were similarly assigned "open area" parameters. Because of limitations in the current conceptual model and code framework, explicit modeling of an open Panel 9 was not done; instead, a quantitative argument for the conservatism (with respect to releases) of including waste in Panel 9 was provided.

For the CCDFGF code, a reassignment of panel neighboring was done for consistency with the modified repository configuration. All of these changes were shown to impact releases for the

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APCS analysis, as well as the CRA19 analysis. Therefore, there is the potential for a substantial impact on the parameter sensitivity analysis. The parameter sensitivity analysis for the APCS analysis is documented in Zeitler et al. (2017).

1.1.3 Summary of Changes to Normalized Releases for the CRA19 Analysis

Changes since the CRA14 analysis, including those to sampled parameters and the repository model described above, have resulted in increased total normalized releases at all probabilities or the CRA19 analysis (Brunell 2019). Additionally, all individual release mechanisms have shown increases since the CRA14 analysis.

1.1.4 STEPWISE Code Update

Calculations for the CRA-2014 PA were performed on the WIPP PA Alpha Cluster (Long 2013). WIPP PA codes were later migrated to the WIPP PA Solaris Cluster (Kirchner 2012, Kirchner et al. 2014, Kirchner et al. 2015). The migration process consisted of recompilation, retesting, and requalification of codes. The STEPWISE code v2.21 was used in CRA-2014 PA calculations and code v2.22 was a product of the migration to the Solaris system. For the CRA19 and CRA14 analyses compared in this document, STEPWISE code v2.22 was used.

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2.0 CONCEPTUAL APPROACH FOR THE CRA-2019

No changes have been made to the conceptualization of parameter sampling since the CRA-2014 PA. Under the standard approach, a determination is first made as to which parameters are epistemically uncertain and parameter distributions are defined for those parameters and entered into the WIPP PA Parameter Database (ParamDB) (Kim and Feng 2019). Uncertain parameters are sampled from these defined distributions using a Latin Hypercube sampling design for three replicates of 100 sets of sampled parameters (Zeitler 2019b). Following the execution of WIPP PA codes for 300 realizations ("vectors") (each of which uses one set of specified parameters), calculated releases are entered into the WIPP PA Results Database (PA_Results). A stepwise linear multiple regression ("sensitivity") analysis is then performed to determine the relative importance of the sampled parameters on the calculated mean releases. The sensitivity analysis is used to resolve the question of which *sampled* parameters contribute the most to the variability (uncertainty) observed in the mean releases by vector. The sensitivity analysis performed using stepwise regression cannot be used to explain sensitivity of the results to the changes implemented in the models, fixed parameters and inventory components of a WIPP PA analysis.

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3.0 PARAMETER SENSITIVITY ANALYSIS METHODOLOGY

The STEPWISE code is used as part of the sensitivity analysis to determine the relative importance of the sampled parameters in the CRA19 analysis of the CRA-2019 PA. STEPWISE receives sampled input parameter values and calculated release data that correspond to those input parameters on a vector basis. The release data are represented by the means across 10,000 futures for each vector. The STEPWISE code relates the sampled input parameter values to the vector means by performing a multiple regression analysis and reporting the results in tables. Details for the parameter sensitivity analysis methodology are described below.

This report documents the results of the CRA19 sensitivity analysis and shows, for comparison, the results obtained for the CRA14 analysis. Due to changes made between the CRA14 (Rev. 0) analysis and those of the CRA14 (Rev. 2) analysis, there are some differences for the CRA14 analysis between those presented in Kirchner (2013) and those presented here (see also Appendix A).

3.1 Stepwise Linear Multiple Regression

WIPP PA employs stepwise linear multiple regression to evaluate the relative importance of the various sampled parameters on the estimates of potential releases. In the forward stepwise approach used by the STEPWISE code, a sequence of regression models is constructed, starting with the input parameter that has the strongest simple correlation with the output variable. Partial correlations between the output and the remaining variables are then computed. The partial correlations remove the linear effects of variables already included in the model. The variable having the largest significant partial correlation coefficient is added next, and the partial correlations for the remaining input variables are recomputed.

3.1.1 Determination of Significance

Significance is determined using an F-test, and the significance level for adding an input variable to the model is $1 - \alpha_{in}$, where α_{in} is the significance level for a Type I error that is set by the analyst. The F-test compares the variability contributed by the variable to the variability not accounted for by the regression; i.e., the variability of the residuals. By default, the STEPWISE code sets $\alpha_{in} = 0.05$, so that one is 95% confident that there is a partial correlation between the input and output variables. This process is repeated until no remaining variables have significant correlations with the output variable. Variables excluded from the regression model contribute no significant information in relation to the unexplained variability and hence the results are judged to be relatively insensitive to those parameters. The method does not guarantee that the relative contributions of model parameters to the R² (coefficient of determination) will always be smaller with increasing rank but this is often the case.

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3.1.2 Regression Coefficients

Input variables that are added to the regression model are not necessarily retained. For an input variable to be retained, its regression coefficient (i.e. the linear contribution of an input to the prediction of the output variable) must be statistically distinguishable from zero. A t-test is used to determine whether a regression coefficient is significantly different than zero. The t-test evaluates the null hypothesis that the regression coefficient is zero. The hypothesis is not rejected when random effects can give rise to the observed regression coefficient with probability α_{out} . The random effects are caused by the stochastic variability contributed by the input variables not in the regression model. In other words, the hypothesis is rejected, and the variable is included in the model when the $1 - \alpha_{out}$ confidence interval of the regression coefficient does not encompass zero.

By default, the α_{out} value used by the STEPWISE code for allowing a variable to enter the regression model is 0.05. Thus, in the default case, one is 95% confident that the input variables make a linear contribution to the response of the output variable. The user may specify different α -values in the input control file. However, the value allowing a variable to enter the model, α_{in} , must be less than or equal to the value by which a variable is allowed to leave the model, α_{out} , to avoid looping. In the sensitivity analysis calculations performed for the CRA19 analysis, α_{in} was 0.05, and α_{out} was 0.05.

3.1.3 Predicted Error Sum of Squares

The predicted error sum of squares (PRESS) is computed to detect over-fitting of the regression model to the data. Over-fitting can occur when the regression methodology causes the fit to favor specific points rather than the general shape of the data curve. In such a case the minimum value of PRESS may occur earlier than the last step in the regression analysis. No such condition was observed in any of the rank correlation analyses reported herein.

3.2 Parameters Sampled for the CRA-2019 PA

The input files for STEPWISE (Section 3.5.1) use short names for input parameters rather than material:property designations used in other WIPP PA codes. These short names are required because of a limitation in the length of variable names in the STEPWISE code. Table 2 associates these names with the material and property names. For each sampled parameter in the CRA19 analysis, there is an assigned variable.

In addition, three variables are created in STEPWISE through transformation of the GLOBAL:OXSTAT parameter, the indicator variable for actinide oxidation states. The GLOBAL:OXSTAT parameter is sampled as a uniform distribution with range [0,1], but is treated in the BRAGFLO, PANEL, and SECOTP2D codes as a Bernoulli distribution (a distribution having only two discrete states). The computed variable WOXSTAT is assigned 0 if GLOBAL:OXSTAT is less than 0.5 and is assigned 1 otherwise.

The other two computed variables represent the K_{ds} for the different oxidation states of uranium and plutonium considered in WIPP PA. A K_{d} value represents the matrix:water partitioning

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coefficient. If WOXSTAT is 0, then the CMKDU variable is assigned the sampled value of U+4:MKD_U and CMKDPU is assigned PU+3:MKD_PU; i.e., the K_ds for the +IV and +III oxidation states of uranium and plutonium, respectively. If WOXSTAT is 1, then the CMKDU variable is assigned the sampled value of U+6:MKD_U and CMKDPU is assigned PU+4:MKD_PU; i.e., the K_ds for the +VI and +IV oxidation states of uranium and plutonium, respectively. This is done because some sampled parameter values are not used in WIPP PA calculations depending on the sampled value of the GLOBAL:OXSTAT parameter. In the discussion below, these variables are referenced as (Composite):MKD_U and (Composite):MKD_PU in order to denote their status as composites of pairs of sampled parameters.

Material	Property	Variable Name	Description
AM+3	MKD_AM	CMKDAM3	Americium III, matrix partition coefficient for americium
BH_SAND	PRMX_LOG	BHPERM	Borehole filled with silty sand, log of intrinsic permeability, x-direction
BOREHOLE	DOMEGA	DOMEGA	Borehole and fill, drill string angular velocity (0)
BOREHOLE	TAUFAIL	WTAUFAIL	Borehole and fill, effective shear strength for erosion
CASTILER	COMP_RCK	BPCOMP	Castile brine reservoir, bulk compressibility
CASTILER	PRESSURE	BPINTPRS	Castile brine reservoir, brine far-field pore pressure
CASTILER	PRMX_LOG	BPPRM	Castile brine reservoir, log of intrinsic permeability, x-direction
CONC_PLG	PRMX_LOG	PLGPRM	Concrete plug, surface and rustler, log of intrinsic permeability, x-direction
CULEBRA	APOROS	CFRACPOR	Culebra member of the rustler formation, Culebra advective porosity
CULEBRA	DPOROS	CMTRXPOR	Culebra member of the rustler formation, diffusive porosity for Culebra dolomite
CULEBRA	HMBLKLT	CFRACSP	Culebra member of the rustler formation, Culebra half matrix-block length
CULEBRA	MINP_FAC	CTRANSFM	Culebra member of the rustler formation, mining transmissivity multiplier

Table 2 – Material and Property Names Associated with VariableNames Used in the CRA-2019 PA Sensitivity Analysis

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Material	Property	Variable Name	Description
DRZ_1	PRMX_LOG	DRZPRM	Disturbed rock zone during the time period that begins with facility closure (0 years) and ends when DRZ healing is complete, log of intrinsic permeability, x-direction
DRZ_PCS	PRMX_LOG	DRZPCPRM	DRZ directly above the panel closure system, log of intrinsic permeability, x- direction
GLOBAL	CLIMTIDX	CCLIMSF	Information that applies globally, climate index
GLOBAL	GDEPFAC	GDEPFAC	Information that applies globally, energy deposition probability for wetted solid radionuclides
GLOBAL	OXSTAT	WOXSTAT	Information that applies globally, index for the oxidation state
GLOBAL	PBRINE	PBRINE	Information that applies globally, prob. that drilling intrusion in excavated area encounteres pressurized brine
GLOBAL	TRANSIDX	CTRAN	Information that applies globally, index for selecting realizations of the transmissivity field
PCS_T1	PORE_DIS	T1PDIS	Panel closure system for an initial time duration, Brooks-Corey pore distribution parameter
PCS_T1	POROSITY	T1POROS	Panel closure system for an initial time duration, effective porosity
PCS_T1	PRMX_LOG	TIPRMX	Panel closure system for an initial time duration, log of intrinsic permeability, x- direction
PCS_T1	SAT_RBRN	T1SRBRN	Panel closure system for an initial time duration, residual brine saturation
PCS_T1	SAT_RGAS	TISRGAS	Panel closure system for an initial time duration, residual gas saturation
PCS_T2	POR2PERM	T2P2PERM	Panel closure system for a secondary time duration, distribution used to calculate permeability from sampled porosity values

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Material	Property	Variable Name	Description
PCS_T2	POROSITY	T2POROS	Panel closure system for a secondary time duration, effective porosity
PCS_T3	POROSITY	T3POROS	Run-of-mine panel closure system, tertiary time period, effective porosity
PU+3	MKD_PU	CMKDPU3	Plutonium III, matrix partition coefficient for plutonium
PU+4	MKD_PU	CMKDPU4	Plutonium IV, matrix partition coefficient for plutonium
S_HALITE	COMP_RCK	HALCROCK	Salado halite, intact, bulk compressibility
S_HALITE	POROSITY	HALPOR	Salado halite, intact, effective porosity
S_HALITE	PRESSURE	SALPRES	Salado halite, intact, brine far-field pore pressure
S_HALITE	PRMX_LOG	HALPRM	Salado halite, intact, log of intrinsic permeability, x-direction
S_MB139	PORE_DIS	ANHBCEXP	Salado marker bed 139, intact and fractured, Brooks-Corey pore distribution parameter
S_MB139	PRMX_LOG	ANHPRM	Salado marker bed 139, intact and fractured, log of intrinsic permeability, x-direction
S_MB139	RELP_MOD	ANHBCVGP	Salado marker bed 139, intact and fractured, model number, relative permeability model
S_MB139	SAT_RBRN	ANRBRSAT	Salado marker bed 139, intact and fractured, residual brine saturation
SHFTL_T1	PRMX_LOG	SHLPRM2	Lower portion of simplified shaft from 0 - 200 years, log of intrinsic permeability, x- direction
SHFTL_T2	PRMX_LOG	SHLPRM3	Lower portion of simplified shaft from 200 - 10,000 years, log of intrinsic permeability, x-direction
SHFTU	PRMX_LOG	SHUPRM	Upper portion of simplified shaft, log of intrinsic permeability, x-direction

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		Variable	
Material	Property	Name	Description
SHFTU	SAT_RBRN	SHURBRN	Upper portion of simplified shaft, residual brine saturation
SHFTU	SAT_RGAS	SHURGAS	Upper portion of simplified shaft, residual gas saturation
SOLMOD3	SOLVAR	WSOLVAR3	Oxidation state III model, solubility multiplier
SOLMOD4	SOLVAR	WSOLVAR4	Oxidation state IV model, solubility multiplier
SPALLMOD	PARTDIAM	SPPDIAM	Material developed for DRSPALL, particle diameter of disaggregated waste
SPALLMOD	REPIPERM	REPIPERM	Material developed for DRSPALL, waste permeability to gas local to intrusion borehole
SPALLMOD	REPIPOR	SPLRPOR	Material developed for DRSPALL, waste porosity at time of drilling intrusion
SPALLMOD	TENSLSTR	TENSLSTR	Material developed for DRSPALL, tensile strength of waste
STEEL	CORRMCO2	WGRCOR	Generic steel in waste, inundated corrosion rate for steel without CO2 present
STEEL	HUMCORR	HUMCORR	Generic steel in waste, humid corrosion rate for steel
TH+4	MKD_TH	CMKDTH4	Thorium IV, matrix partition coefficient for thorium
U+4	MKD_U	CMKDU4	Uranium IV, matrix partition coefficient for uranium
U+6	MKD_U	CMKDU6	Uranium VI, matrix partition coefficient for uranium
WAS_AREA	BIOGENFC	WBIOGENF	Waste emplacement area and waste, probability of attaining sampled microbial- gas-generation rates
WAS_AREA	BRUCITEC	WBRUITEC	Waste emplacement area and waste, MgO inundated hydration rate in ERDA-6 brine
WAS_AREA	BRUCITEH	WBRUITEH	Waste emplacement area and waste, MgO humid hydration rate

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Material	Property	Variable Name	Description
WAS_AREA	BRUCITES	WBRUITES	Waste emplacement area and waste, MgO inundated hydration rate in GWB brine
WAS_AREA	GRATMICH	WGRMICH	Waste emplacement area and waste, humid biodegradation rate for cellulose
WAS_AREA	GRATMICI	WGRMICI	Waste emplacement area and waste, inundated biodegradation rate for cellulose
WAS_AREA	HYMAGCON	WHYMAGC	Waste emplacement area and waste, rate of conversion of hydromagnesite to magnesite
WAS_AREA	PROBDEG	WMICDFLG	Waste emplacement area and waste, probability of plastics and rubber biodegradation in event of microbial gas generation
WAS_AREA	SAT_RBRN	WRBRNSAT	Waste emplacement area and waste, residual brine saturation
WAS_AREA	SAT_RGAS	WRGSSAT	Waste emplacement area and waste, residual gas saturation
WAS_AREA	SAT_WICK	WASTWICK	Waste emplacement area and waste, index for computing wicking

3.3 Limitations of the Analysis

For clarity on the scope of the analysis, some details on the limitations of the analysis are laid out in the subsections below.

3.3.1 Linear Regression Model

The STEPWISE sensitivity analysis constructs a multivariate linear regression model. One of the assumptions of this statistical model is that the dependent (output) variable shows a linear response to the independent (input) variables. In cases where the response is non-linear but monotonic, replacing the values of the data with their ranks tends to linearize the response curves and standardizes the variability in the outputs and parameters by mapping the data into identical ranges.

The rank of a value is an integer representing its position in the sorted list of the values. Ranking also tends to de-emphasize the impact of "outliers," which are points having considerably larger or smaller values than the remainder of the sample population. Although the use of ranks precludes using the model to predict values of an output variable given an input variable, the results are usually well suited for ranking the importance of the contributions of the input variables to the response of the output variable. The STEPWISE code has the functionality to

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perform ranked regressions, but that was not used here. A previous analysis using ranked regression showed stronger correlations than the regressions based on the unranked data, which suggested that there are non-linear relationships between the dependent and independent variables, but it does not eliminate the possibility that there are also non-monotonic relationships (Kirchner 2013).

3.3.2 Scarcity of Data

There are also cases (e.g., releases from the Culebra and spallings releases) where large proportions of the vectors in each replicate show no credible release values (values > 0.0001 EPA units) or zero releases (Table 3 and Table 4). Values less than 0.0001 EPA units are considered to be dominated by numerical error and hence often unreliable. In terms of ranking the relative importance of the parameters, the issue of a large proportion of zeros or unreliable values is most problematic. For comparison, corresponding data for the CRA14 analysis are found in Appendix A.

Table 3 – Percentage of V	Vectors With	Maximum	Release	Exceeding 0
and 0.0001 EPA Units				

Release Type		Replicate 1		Replicate 2		licate 3
Release Type	>0	≥0.0001	>0	≥0.0001	>0	≥0.0001
Cuttings and Cavings	100	100	100	100	100	100
Direct Brine	100	97	100	97	100	96
Spallings	64	64	58	57	56	56
Total	100	100	100	100	100	100
Total From Culebra	92	9	95	13	97	9
Total To Culebra	92	75	95	80	97	76

Table 4 – Percentage of Vec	tors With Mean	n Release Exceeding	g 0 and
0.0001 EPA Units			

Polosso Typo		Replicate 1		Replicate 2		licate 3
Release Type	>0	≥0.0001	>0	≥0.0001	>0	≥0.0001
Cuttings and Cavings	100	100	100	100	100	100
Direct Brine	100	90	100	92	100	90
Spallings	64	47	58	46	56	48
Total	100	100	100	100	100	100
Total From Culebra	92	5	95	6	97	6
Total To Culebra	92	63	95	68	97	64

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3.3.3 Spurious Correlations

Setting the STEPWISE parameter α_{out} to α_{in} (see Section 3.0) maximizes the number of variables in the model (as requested by EPA in C-23-18, U.S. Environmental Protection Agency 2004) but can increase the number of spurious correlations (Kirchner 2004a, Kirchner 2004b). A spurious correlation implies a linear relationship exists between two variables but in reality no such relationship exists.

3.3.4 Statistical Significance

Most of the regression models produced by the STEPWISE code do not include all of the input variables, even after ranking the data. This simply indicates that the uncertainties in many of the parameters have statistically insignificant effects on the output variable. Statistical insignificance can arise because the output variable has a low functional response to the input variable, because the magnitude of uncertainty in the input variable is small relative to the other inputs, or from a combination of both conditions. This is not to say that these non-significant variables have no influence on the releases. Their exclusion from the tables reflects the inability of this statistical technique to rank their importance with an acceptable degree of confidence. For example, if the response of the output variable to an input variable was non-monotonic then the regression analysis might fail to properly identify that variable's importance.

In addition, the stochastic processes modeled introduce variability that cannot be attributed to the sampled parameters so the regression analyses cannot be expected to explain all of the observed variability in the vector means. In the case of the WIPP releases, the stochastic effects of drilling and mining intrusions (aleatory uncertainty) contribute to the variability in the release estimates. In the CRA19 analysis, 56% to 74% of the variability in the total releases has been accounted for by the sampled input variables as measured by the R² value (Table 5).

Release Type		CRA14		CRA19			
	Rep. 1	Rep. 2	Rep. 3	Rep. 1	Rep. 2	Rep. 3	
Total	0.65	0.77	0.64	0.56	0.68	0.74	
Cuttings and Cavings	0.75	0.84	0.84	0.68	0.76	0.83	
Spallings	0.55	0.59	0.63	0.64	0.66	0.71	
Direct Brine	0.74	0.78	0.86	0.80	0.80	0.92	
From Culebra	0.71	0.74	0.61	0.70	0.70	0.62	
To Culebra	0.94	0.92	0.94	0.91	0.90	0.91	

Table 5 – Maximum Proportion of the Variability in Releases	
Accounted for in Stepwise Rank Regression	

Often several of the parameters that appear in the regression model contribute very little to the R^2 value and, therefore, explain very little of the variability in the output variable. Parameters that have minor contributions can appear by chance, simply due to random correlations. Many of the

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parameters that account for only a few percent to the variability in an output from one replicate may show different rankings, or can even be absent, in another replicate. Thus, it is difficult to assess the importance of the parameters that improve the regression model very little and, in reality, they may have no importance at all. Therefore, only the parameters that appear to have meaningful impacts on the regression model will be discussed.

3.4 Other Considerations for Interpreting Sensitivity Analysis Results

Interpretation of the results of the parameter sensitivity study can be challenging, given the limitations described above, as well as the influence of model variations apart from sampled parameters. Some of the aspects of WIPP PA that should be kept in mind when interpreting the results in Section 4.0 are described below.

3.4.1 Influence of Stochastic Processes

The mean and variance of the release for a given vector are controlled by the stochastic processes that govern the events in each future. A change in the frequency of a stochastic event such as drilling rate can shift a distribution left or right, thus changing the mean. However, changes that impact the shape of a distribution can also cause changes in the mean.

3.4.2 CCDF Construction Methodology

One potential disconnect between the sensitivity of the vector means to changes in the mean CCDF curves comes, in part, because the mean CCDF curves (Figure 1) are averages of the probabilities for a release, R, across vectors, $p_{R>x}$ at each release level x. That is, for one replicate:

$$\overline{p}_{R>x} = \frac{1}{100} \sum_{1}^{100} p_{R>x}$$
(1)

In other words, the mean CCDF curves are created by averaging vertically the individual CCDF curves for the vectors (Figure 2). This is equivalent to pooling the data from all futures across vectors. The CCDF curves focus attention on the right tails of the distributions of releases rather than the vector means.

On the other hand, the vector means, \overline{R}_{ν} are computed as the average of each release across the 10,000 futures:

$$\overline{R}_{\nu} = \frac{1}{10000} \sum_{i=1}^{10000} R_{\nu,i}$$
⁽²⁾

where $R_{v,i}$ is the release from the *i*th future of vector *v*. Thus one can imagine cases where the vector means for some type of release in one analysis are all greater than the corresponding

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vector means for that release in a second analysis and yet the CCDF curves for the vectors of the first analysis lie to the left of CCDF curves of the vectors of the second analysis.

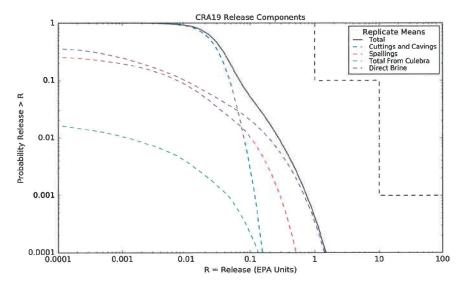


Figure 1 – Mean CCDFs Across Replicates for the CRA19 Analysis

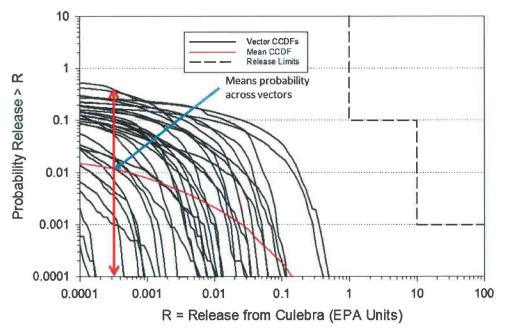


Figure 2 – Relationship Between CCDFs for Individual Vectors and the Mean Probability CCDF

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3.4.3 Impact of Changes in Parameter Distributions

In some cases, the sensitivity of the vector means to the sampled parameters coupled with differences in the distribution of those parameters between analyses can be correlated with the observed differences between analyses in the mean CCDF curves for each type of release. For example, the distribution of a dominant parameter, BOREHOLE:TAUFAIL, was changed between the PABC-2009 and the CRA-2014 and corresponding changes were seen in the mean CCDF curves for cuttings and cavings releases (Kirchner 2013). However, changes in constant parameters and changes in the stochastic processes (e.g., timing of drilling intrusions) can also impact the means of the vectors. Thus, such correlations are not guaranteed and counterintuitive results are possible due impacts beyond changes to sampled parameters.

3.5 Run Control

A full description of the run control for the CRA19 analysis, including names and locations of input and output files, can be found in Long (2019). As outlined in AP-181 (Zeitler 2019a), in cases where comparisons are made to the CRA-2014 PA results, the CRA14 (Rev. 2) results from the Solaris migration integration tests are used (Kirchner et al. 2014, Kirchner et al. 2015). A run of the STEPWISE code was not part of the migration integration tests for Revision 2 of the CRA-2014 calculations, but has been done here to facilitate a comparison with CRA19 results (see Appendix A).

3.5.1 STEPWISE Input Files

Input files and run scripts for the STEPWISE code were generated using the *PA_AnalysisRemote.accdb* Microsoft Access database that has links to the WIPP PA Results Database (PA_Results) and WIPP PA Parameter Database (ParamDB), as described in Long (2019). A copy of the *PA_AnalysisRemote.accdb* database is included in a directory with the final output tables. The input files contain mean release values and LHS-sampled values from the CRA19 analysis, all of which were obtained from the PA_Results database. An identical process was followed to generate input files for the CRA14 analysis of the STEPWISE code.

3.5.2 STEPWISE Output Files

One output text file was generated for each replicate of the CRA19 and CRA14 analyses. The *PA_AnalysisRemote.accdb* database was then used to analyze the results of the STEPWISE runs, producing an *rtf* file readable by Microsoft Word containing data in output table format. The data in the output tables are presented in Sections 4.1 through 4.5.



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4.0 RESULTS

This section describes the results of the stepwise regression analysis for the sampled parameters used in the CRA19 analysis as they impact each individual release mechanism tracked by the CCDFGF code, as well as the total releases. Additionally, the impacts on direct brine volumes and releases to the Culebra are also described. The results are largely presented in tables that indicate those parameters that contribute most significantly to the total variation of observed PA outputs. Results from the CRA19 analysis are compared to those from the CRA14 (Rev. 2) (hereafter CRA14) analysis.

In the tables below, the cumulative R^2 value represents the proportion of total variation explained by the fitted regression using the listed variables, starting with the greatest contributor to the variance. The number of variables used in the regression model is determined by the stepwise regression analysis, as discussed above. Regression analyses are conducted for each replicate separately, so results for the CRA14 and CRA19 analyses are therefore compared on a replicate basis.

To aid in interpretation and discussion of the results, parameters with ΔR^2 values (the difference in R^2 between the current step and the previous step) greater than 0.05 are highlighted in the tables below. While this threshold is somewhat arbitrary, those highlighted parameters are clearly influential and tend to have a more consistent ranking.

4.1 Cuttings and Cavings Releases

Cuttings and cavings releases are due to solids releases during an intrusion and are combined as outputs from the CCDFGF code. Cuttings and cavings releases are the product of cuttings and cavings volumes and waste stream concentrations. Cuttings volumes calculated by the CUTTINGS_S code are controlled by the drill bit diameter whereas cavings volumes depend on the sampled parameters BOREHOLE:TAUFAIL (waste shear strength) and BOREHOLE:DOMEGA (angular velocity of the drill string). The distribution for the BOREHOLE:TAUFAIL parameter is slightly changed compared to the CRA14 analysis (Zeitler 2019a). The distribution for the BOREHOLE:DOMEGA parameter is the same as that for the CRA14 analysis. The uncertainty in mean cuttings and cavings releases is due to the uncertainty in the cuttings and cavings volumes (Kicker 2019a) as well as the variation in solids release concentrations (i.e., waste stream concentrations) (Kicker 2019b).

4.1.1 Changes in Releases Since the CRA14 Analysis

Cuttings and cavings releases for CRA19 show an overall increase compared to those of the CRA14 analysis (Brunell 2019). The increased releases are a product of increased cuttings and cavings release volumes (Brunell 2019) and a new mix of CH waste stream concentrations and volumes provided by an updated radionuclide inventory (Kicker 2019b). Cuttings and cavings releases have increased in large part due to an increased drilling intrusion rate (Brunell 2019).

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4.1.2 Regression Analysis Results

Table 6 through Table 8 compare the parameters that showed significant correlations to mean cuttings and cavings releases for the CRA14 and CRA19 analyses based on a stepwise regression using ranked data.

Waste shear strength (BOREHOLE:TAUFAIL) controls about 59-63 % of the variability in mean cuttings and cavings releases for the CRA19 analysis compared to 65-72 % for the CRA14 analysis. This reduced contribution is not attributable to the very small change in the distribution of BOREHOLE:TAUFAIL for the CRA19 analysis (Kicker 2019a), but may be more closely related to the variation in the distribution of contact-handled (CH) waste stream concentrations, which are not based on sampled parameters, but are randomly sampled by the CCDFGF code based on waste stream volume when cuttings and cavings releases are calculated (Kicker 2019b). Additionally, cuttings and cavings releases are impacted by the rate of intrusion of the repository, which is not a sampled variable but nonetheless provides input into the stochastic timing of intrusions and thus variation in the conditions (i.e., concentrations vary with time) of intrusion events.

The angular velocity of the drill string (BOREHOLE:DOMEGA) controls about 6-7 % of the variability in mean cuttings and cavings releases for the CRA19 analysis compared to 6-8 % for the CRA14 analysis. This difference is not substantial.

The remaining parameters in Table 6 through Table 8 each explain less than about 1-2 % of the variability in cuttings and cavings and are undoubtedly spurious since they have no functional influence on cuttings and cavings releases as currently calculated for WIPP PA.

Table 6 – Stepwise Ranked Regression Analysis for Mean Cuttings and Cavings Releases, Replicate 1 of the CRA14 and CRA19 Analyses

	CRA14 Replicate 1			CRA19 Replicate 1				
Step ^a	Variable ^b	R ^{2c}	SRRC ^d	Variable	R ²	SRRC		
1	BOREHOLE:TAUFAIL	0.65	-0.82	BOREHOLE:TAUFAIL	0.59	-0.76		
2	BOREHOLE:DOMEGA	0.71	0.25	BOREHOLE:DOMEGA	0.66	0.27		
3	(Composite):MKD_U	0.74	-0.16	PCS_T1:PRMX_LOG	0.68	-0.14		
4	SHFTU:SAT_RBRN	0.75	0.11					

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^C Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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Table 7 – Stepwise Ranked Regression Analysis for Mean Cuttings and Cavings Releases, Replicate 2 of the CRA14 and CRA19 Analyses

	CRA14 Replicate 2			CRA19 Replicate 2			
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable R ²		SRRC	
1	BOREHOLE:TAUFAIL	0.72	-0.84	BOREHOLE:TAUFAIL	0.61	-0.77	
2	BOREHOLE:DOMEGA	0.78	0.26	BOREHOLE:DOMEGA	0.67	0.26	
3	PCS_T2:POR2PERM	0.81	0.17	PCS_T2:POR2PERM	0.70	0.16	
4	PHUMOX3:PHUMCIM	0.82	-0.11	CASTILER:PRMX_LOG	0.71	0.12	
5	CASTILER:PRMX_LOG	0.83	0.09	WAS_AREA:BRUCITEC	0.72	0.12	
6	S_HALITE:PRMX_LOG	0.84	0.08	(Composite):OXSTAT	0.74	0.11	
7	SOLMOD4:SOLVAR	0.84	-0.08	S_HALITE:PRESSURE	0.75	0.11	
8				WAS_AREA:SAT_RBRN	0.76	0.10	

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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	CRA14 Replic	Replicate 3 CRA19 Replicate 3				
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable R ²		SRRC
1	BOREHOLE:TAUFAIL	0.65	-0.79	BOREHOLE:TAUFAIL	0.63	-0.79
2	BOREHOLE:DOMEGA	0.73	0.31	BOREHOLE:DOMEGA	0.69	0.25
3	CULEBRA: APOROS	0.75	0.13	GLOBAL:OXSTAT	0.72	0.19
4	S_HALITE:POROSITY	0.77	0.11	STEEL:HUMCORR	0.74	0.15
5	S_MB139:SAT_RBRN	0.78	-0.10	SHFTL_T2:PRMX_LOG	0.76	0.12
6	SHFTU:SAT_RBRN	0.79	-0.11	PCS_T1:SAT_RBRN	0.77	0.12
7	SOLMOD4:SOLVAR	0.80	-0.09	CULEBRA:HMBLKLT	0.78	0.12
8	SPALLMOD:REPIPERM	0.81	0.10	WAS_AREA:SAT_WICK	0.79	0.12
9	WAS_AREA:BRUCITEH	0.82	0.10	AM+3:MKD_AM	0.80	-0.11
10	(Composite):OXSTAT	0.83	0.09	PCS_T2:POROSITY	0.81	-0.10
11	PCS_T1:POROSITY	0.84	0.09	CONC_PLG:PRMX_LOG	0.82	-0.10
12				SPALLMOD:REPIPOR	0.83	0.09

Table 8 – Stepwise Ranked Regression Analysis for Mean Cuttings and Cavings Releases, Replicate 3 of the CRA14 and CRA19 Analyses

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

4.2 Spallings Releases

Spallings releases are additional solids releases during an intrusion event and are calculated as the product of spallings volumes and the average concentration of CH waste at the time of intrusion. Spallings volumes calculated by the DRSPALL and CUTTINGS_S codes are directly impacted by gas pressures in the repository and the sampled parameters

SPALLMOD: PARTDIAM (the particle diameter for disaggregated waste),

SPALLMOD:REPIPOR (waste porosity), SPALLMOD:REPIPERM (waste permeability), and SPALLMOD:TENSLSTR (tensile strength of the waste). The distributions of the sampled parameters are the same as in the CRA14 analysis. Spallings releases are also indirectly impacted by other parameters and aspects of the repository representation that impact repository pressures.

4.2.1 Changes in Releases Since the CRA14 Analysis

Spallings releases for CRA19 show an overall increase compared to those of the CRA14 analysis (Brunell 2019). The increased releases are a product of increased spallings release volumes (Brunell 2019) and spallings concentrations that have stayed approximately the same (Kicker

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2019b). Across replicates, the number of vectors having spallings releases in the CRA19 that exceeded 0.0001 was greater than that from the CRA14 analysis (Table 3). Spallings releases have increased primarily due to increased repository pressures (Kicker 2019a)¹.

4.2.2 Regression Analysis Results

Table 9 through Table 11 compare the parameters that showed significant correlations to mean spallings releases for the CRA14 and CRA19 analyses based on a stepwise regression using ranked data. The number of nonzero spallings releases (Table 3 and Table 4) has decreased, but is still low enough to reduce the effectiveness of the regression analysis, as a large number of zero values in the data tend to negate the assumption of linear regression that errors (residuals) are normally distributed (see Section 3.1.1). In addition, the distribution of zeros along the independent axis can exert substantial control on the slope of the regression model.

The dominant parameter with regard to controlling spallings releases in the CRA19 analysis is BH_SAND:PRMX_LOG (the (logarithm of the) permeability of the silty-sand-filled borehole) for all three replicates.² The CRA19 results indicate a stronger and more consistent influence of BH_SAND:PRMX_LOG compared to the CRA14 analysis, with this parameter controlling about 19-23 % of the variability in spallings releases compared to 2-15 % for the CRA14 analysis. A scatterplot of BH_SAND:PRMX_LOG versus spallings mean release values is shown in Figure 3 for both the CRA14 and CRA19 analyses and illustrates the increased response in the CRA19 analysis. The negative SRRC values indicate that lower borehole permeability values correlate with larger mean release values. This is because lower sand-filled borehole permeability values allow for larger pressure buildup in the waste areas after a primary intrusion, and larger pressure values can propel more spallings (waste solids) into and up a wellbore during a secondary intrusion. The increased influence of the BH_SAND:PRMX_LOG parameter on spallings releases may be attributed to the increased repository pressures (and therefore increased impact on spallings) observed in the CRA19 analysis (Day 2019).

In addition, a reduced influence of the CASTILER:PRESSURE (the initial brine pressure in the Castile brine reservoir) is seen across all three replicates via decreased ΔR^2 and SRRC values.

The SPALLMOD:REPIPERM and SPALLMOD:PARTDIAM parameters continue to be impactful on variability of spallings releases, with the SPALLMOD:REPIPERM contribution increasing for all replicates. The importance of the SPALLMOD:REPIPERM parameter has increase because of the correction of an error in the DRSPALL code (see Appendix A).

The new GLOBAL:GDEPFAC parameter (energy deposition probability for wetted solid radionuclides) distribution, which plays a role in radiolytic gas generation, shows no impact on the variability of spallings releases for any of the three replicates (Figure 4).

¹ A correction to an error in the DRSPALL code also resulted in increased spallings volumes (Kicker et al. 2015), but that was accounted for in the CRA14 (Rev. 2) results. Comparison of the results from the parameter sensitivity analysis for spallings releases for the CRA-2014 PA calculations and the CRA14 analysis (i.e., due to correction to the DRSPALL code) is presented in Appendix A.

² Although the BH_SAND:PRMX_LOG parameter is defined for the "X" direction, the permeabilities for the Y and Z directions are assigned the same values as those sampled for the X direction in WIPP PA calculations.



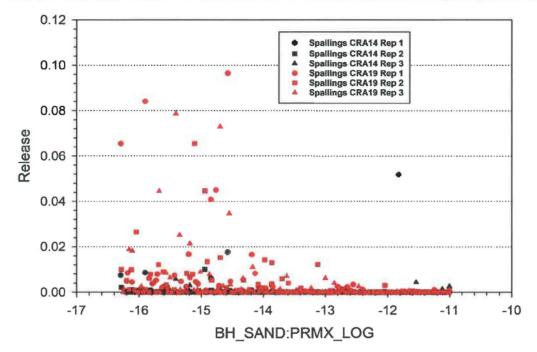


Figure 3 – Scatterplot of (the Logarithm of) Borehole Permeability Versus Mean Spallings Releases for CRA14 and CRA19 Analyses

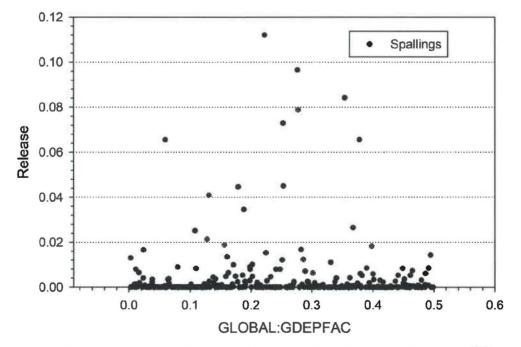


Figure 4 – Scatterplot of Energy Deposition Probability for Wetted Solid Radionuclides Versus Mean Spallings Releases for the CRA19 Analysis

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Table 9 – Stepwise Ranked Regression Analysis for Mean Spallings Releases, Replicate 1 of the CRA14 and CRA19 Analyses

	CRA14 Replic	cate 1		CRA19 Replicate 1				
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC		
1	CASTILER:PRESSURE	0.13	0.37	BH_SAND:PRMX_LOG	0.22	-0.50		
2	SPALLMOD:PARTDIAM	0.24	-0.33	SPALLMOD:REPIPERM	0.38	0.41		
3	SPALLMOD:REPIPERM	0.34	0.32	SPALLMOD:PARTDIAM	0.48	-0.30		
4	BH_SAND:PRMX_LOG	0.40	-0.25	S_HALITE:POROSITY	0.52	0.19		
5	S_HALITE:POROSITY	0.45	0.22	WAS_AREA:BRUCITEH	0.54	0.18		
6	SPALLMOD:REPIPOR	0.48	-0.19	WAS_AREA:PROBDEG	0.56	0.17		
7	WAS_AREA:PROBDEG	0.51	0.17	SOLMOD3:SOLVAR	0.58	0.15		
8	DRZ_PCS:PRMX_LOG	0.53	-0.16	SHFTU:SAT_RGAS	0.60	0.15		
9	(Composite):OXSTAT	0.55	-0.15	(Composite):OXSTAT	0.62	-0.13		
10				CASTILER:PRESSURE	0.64	0.13		

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^C Cumulative Rvalue with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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Table 10 – Stepwise Ranked Regression Analysis for Mean Spallings Releases, Replicate 2 of the CRA14 and CRA19 Analyses

	CRA14 Replicate 2			CRA19 Replicate 2		
Step ^a	Variable ^b	R ^{2c}	SRRC ^d	Variable	R ²	SRRC
1	BH_SAND:PRMX_LOG	0.15	-0.40	BH_SAND:PRMX_LOG	0.23	-0.48
2	SPALLMOD:REPIPERM	0.29	0.36	SPALLMOD:REPIPERM	0.39	0.39
3	CASTILER:PRESSURE	0.40	0.34	GLOBAL:PBRINE	0.45	0.26
4	S_HALITE:POROSITY	0.47	0.28	CASTILER:PRESSURE	0.50	0.23
5	WAS_AREA:SAT_WICK	0.51	0.18	SPALLMOD:PARTDIAM	0.54	-0.19
6	WAS_AREA:BIOGENFC	0.54	0.17	S_HALITE:POROSITY	0.59	0.21
7	SPALLMOD:PARTDIAM	0.56	-0.17	WAS_AREA:SAT_WICK	0.61	0.17
8	GLOBAL:PBRINE	0.59	0.17	WAS_AREA:GRATMICI	0.63	0.14
9				(Composite):MKD_U	0.65	0.13
10				WAS_AREA:BRUCITEC	0.66	-0.12

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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Table 11 – Stepwise Ranked Regression Analysis for Mean Spallings	
Releases, Replicate 3 of the CRA14 and CRA19 Analyses	

	CRA14 Replicate 3			CRA19 Replicate 3		
Step ^a	Variable ^b	R ^{2c}	SRRC ^d	Variable	R ²	SRRC
1	CASTILER:PRESSURE	0.16	0.39	BH_SAND:PRMX_LOG	0.19	-0.47
2	SPALLMOD:PARTDIAM	0.29	-0.34	SPALLMOD:PARTDIAM	0.33	-0.33
3	SPALLMOD:REPIPERM	0.41	0.33	SPALLMOD:REPIPERM	0.47	0.37
4	S_HALITE:POROSITY	0.49	0.28	SPALLMOD:REPIPOR	0.51	-0.22
5	DRZ_PCS:PRMX_LOG	0.52	-0.18	S_HALITE:POROSITY	0.54	0.15
6	PCS_T1:SAT_RBRN	0.55	-0.15	DRZ_1:PRMX_LOG	0.57	-0.17
7	GLOBAL:CLIMTIDX	0.57	0.15	GLOBAL:CLIMTIDX	0.59	0.15
8	BH_SAND:PRMX_LOG	0.59	-0.14	CASTILER:PRESSURE	0.62	0.17
9	SPALLMOD:REPIPOR	0.61	-0.15	WAS_AREA:PROBDEG	0.65	0.16
10	PCS_T1:POROSITY	0.63	-0.14	PCS_T2:POR2PERM	0.66	-0.13
11				SHFTL_T2:PRMX_LOG	0.68	0.14
12				GLOBAL:PBRINE	0.70	0.13
13				S_HALITE:PRESSURE	0.71	-0.13

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^C Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

4.3 Direct Brine Release

Direct brine releases (DBRs) are releases of contaminated brine originating in the repository and flowing up an intrusion borehole during the period of drilling and before the hole is plugged. DBRs are calculated as the product of the direct brine release volume and the concentration of radionuclides within the brine at the time of intrusion. The repository pressure near the drilling location must exceed the hydrostatic pressure of the drilling fluid, which is specified to be 8 MPa in WIPP PA. The brine saturation in the intruded panel must exceed the residual brine saturation of the waste, a sampled parameter (WAS_AREA:SAT_RBRN) in WIPP PA. Because DBRs depend on both waste area pressures and saturations, a number of sampled parameters impact their release values. For the CRA19 analysis, in addition to changes to sampled parameter changes (see Section 1.1.1), repository model changes (see Section 1.1.2) also have impacted DBR releases (Bethune 2019).

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4.3.1 Changes in Releases Since the CRA14 Analysis

Direct brine releases for the CRA19 analysis show an overall increase compared to those of the CRA14 analysis (Brunell 2019). The increased DBRs are a product of increased DBR volumes (Brunell 2019) and decreased radionuclide concentrations in brine (Sarathi 2019). DBR volumes have increased due to increased repository pressures and saturations as a result of increased communication among panels in the South of the repository following the removal of panel closures in that area (Day 2019 and Bethune 2019).

4.3.2 Regression Analysis Results

Table 12 through Table 14 compare the parameters that showed significant correlations to mean DBRs for the CRA14 and CRA19 analyses based on a stepwise regression using ranked data.

The dominant parameter with regard to controlling DBRs in the CRA19 analysis continues to be SOLMOD3:SOLVAR (solubility multiplier for III oxidation states) for all three replicates with this parameter controlling 38-43 % of the variability in DBRs. This level of control is similar to that observed for the CRA14 analysis (35-56 %) for the same parameter, even though the parameter distribution has changed substantially since the CRA14 analysis (Zeitler 2019b).

In addition, the CASTILER:PRESSURE parameter (the initial brine pressure in the Castile brine reservoir) continues to show the second-most control on variability for DBRs across all three replicates at about the same level of control (13-18 % versus 6-18 % for the CRA14 analysis).

The STEEL:CORRMCO2 parameter (the inundated iron corrosion rate), which has an updated and expanded distribution for the CRA19 analysis, has increased in terms of control on variability from less than 1 % for the CRA14 analysis up to 6-7 % for the CRA19 analysis. This is a reversal of the impact observed in the CRA-2014 PA when the parameter distribution had also been updated (Kirchner 2013). A scatterplot of STEEL:CORRMCO2 versus DBR mean release values is shown in Figure 5 for both the CRA14 and CRA19 analyses and illustrates the increased response in the CRA19 analysis. This parameter shows negative values of SRRC for all three replicates, indicating that higher corrosion rates lead to lower DBRs. One mechanism for the observed phenomenon is through reduced waste area saturations as a result of increased pressures caused by increased iron corrosion (and thus gas generation) rates.

The GLOBAL:PBRINE parameter (probability that a drilling intrusion penetrates the pressurized brine in the Castile), which also has an updated and expanded distribution for the CRA19 analysis, has also increased in terms of control on variability from less than 1 % for the CRA14 analysis up to 4-7 % for the CRA19 analysis. This is a reversal of the impact observed in the CRA-2014 PA when the parameter distribution had also been updated (Kirchner 2013). A scatterplot of GLOBAL:PBRINE versus DBR mean release values is shown in Figure 6for both the CRA14 and CRA19 analyses and illustrates the increased response in the CRA19 analysis. This parameter shows positive values of SRRC for all three replicates, indicating that higher brine probabilities lead to higher DBRs. This is consistent with the use of the parameter.

The WAS_AREA:SAT_RBRN (waste area residual brine saturation), which factors directly into the occurrence of DBRs, showed slightly increased influence on the variability from 0-1 % in the CRA14 analysis to a consistent 3 % across all replicates.

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The SOLMOD4:SOLVAR parameter (solubility multiplier for IV oxidation states), which has an updated distribution for the CRA19 analysis, shows only 1-4 % control on the variability of DBRs across three replicates. The STEEL:HUMCORR parameter (humid iron corrosion rate), which was not sampled in the CRA14 analysis, does not appear in the parameter list for any replicate, so it does not have much impact on the variability of DBRs. Similarly, the WAS_AREA:HYMAGCON parameter (hydromagnesite to magnesite conversion rate) does not appear in the parameter list for any replicate. The GLOBAL:GDEPFAC parameter (energy deposition probability for wetted solid radionuclides, which has a role in brine radiolysis), which was not sampled in the CRA14 analysis, shows only a 1 % control in one replicate, so it does not have substantial impact on the variability of DBRs (Figure 7).

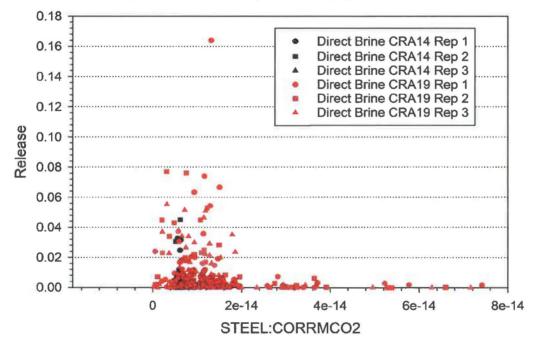


Figure 5 – Scatterplot of Inundated Iron Corrosion Rate Versus Mean Direct Brine Releases for CRA14 and CRA19 Analyses

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 0.18

 0.16

 0.16

 0.14

 0.14

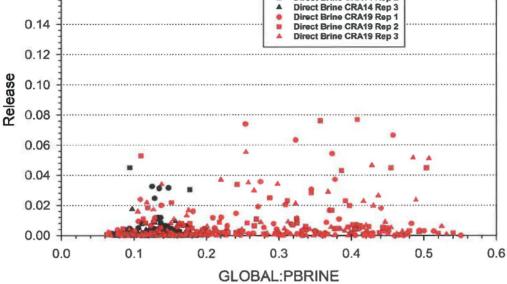


Figure 6 – Scatterplot of Probability of Encountering Brine in Castile Versus Mean Direct Brine Releases

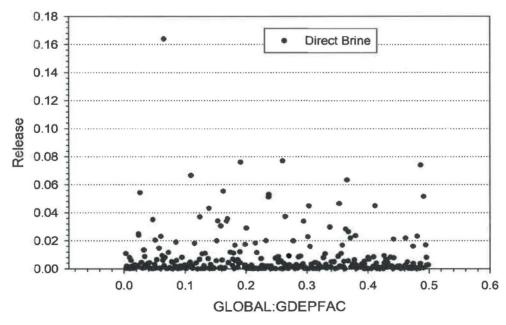


Figure 7 – Scatterplot of Energy Deposition Probability for Wetted Solid Radionuclides Versus Mean Direct Brine Releases for the CRA19 Analysis

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Table 12 – Stepwise Ranked Regression Analysis for Mean Direct Brine Releases, Replicate 1 of the CRA14 and CRA19 Analyses

	CRA14 Replicate 1			CRA19 Replicate 1		
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC
1	SOLMOD3:SOLVAR	0.35	0.59	SOLMOD3:SOLVAR	0.39	0.63
2	CASTILER:PRESSURE	0.53	0.44	CASTILER:PRESSURE	0.57	0.43
3	WAS_AREA:BIOGENFC	0.57	0.21	STEEL:CORRMCO2	0.64	-0.25
4	WAS AREA:PROBDEG	0.61	0.20	GLOBAL:PBRINE	0.68	0.19
5	BH_SAND:PRMX_LOG	0.65	-0.19	BH_SAND:PRMX_LOG	0.71	-0.16
6	S_HALITE:POROSITY	0.68	0.16	CASTILER:COMP_RCK	0.73	0.16
7	S_MB139:RELP_MOD	0.69	-0.16	WAS_AREA:SAT_RBRN	0.76	-0.15
8	S_HALITE:PRMX_LOG	0.71	0.13	S_MB139:RELP_MOD	0.77	-0.11
9	(Composite):OXSTAT	0.72	0.13	WAS_AREA:BIOGENFC	0.79	0.12
10	SOLMOD4:SOLVAR	0.74	0.12	PCS_T3:POROSITY	0.80	0.11

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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Table 13 – Stepwise Ranked Regression Analysis for Mean Direct	
Brine Releases, Replicate 2 of the CRA14 and CRA19 Analyses	

	CRA14 Replie		CRA19 Replicate 2			
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC
1	SOLMOD3:SOLVAR	0.56	0.78	SOLMOD3:SOLVAR	0.38	0.64
2	CASTILER:PRESSURE	0.62	0.23	CASTILER:PRESSURE	0.51	0.33
3	SOLMOD4:SOLVAR	0.66	0.21	GLOBAL:PBRINE	0.57	0.29
4	BH_SAND:PRMX_LOG	0.70	-0.20	STEEL:CORRMCO2	0.64	-0.27
5	GLOBAL:PBRINE	0.73	0.16	BH_SAND:PRMX_LOG	0.67	-0.17
6	SPALLMOD:REPIPOR	0.74	0.13	WAS_AREA:SAT_RBRN	0.70	-0.15
7	S_HALITE:POROSITY	0.76	0.14	SHFTU:SAT_RBRN	0.71	-0.14
8	CASTILER:COMP_RCK	0.78	0.13	CASTILER:COMP_RCK	0.73	0.12
9				GLOBAL:OXSTAT	0.74	-0.12
10				CULEBRA: APOROS	0.75	0.10
11				S_HALITE:POROSITY	0.76	0.10
12				GLOBAL:GDEPFAC	0.77	-0.12
13				DRZ_1:PRMX_LOG	0.78	-0.11
14				WAS_AREA:PROBDEG	0.79	-0.11
15				S_MB139:PRMX_LOG	0.80	0.10

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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	CRA14 Replie	_	CRA19 Replicate 3			
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC
1	SOLMOD3:SOLVAR	0.46	0.64	SOLMOD3:SOLVAR	0.43	0.60
2	CASTILER:PRESSURE	0.64	0.42	CASTILER:PRESSURE	0.57	0.37
3	BH_SAND:PRMX_LOG	0.73	-0.29	BH_SAND:PRMX_LOG	0.68	-0.33
4	DRZ_1:PRMX_LOG	0.76	-0.17	GLOBAL:PBRINE	0.75	0.26
5	(Composite):MKD_U	0.78	-0.15	STEEL:CORRMCO2	0.81	-0.26
6	SOLMOD4:SOLVAR	0.79	0.15	WAS_AREA:SAT_RBRN	0.84	-0.16
7	S_HALITE:POROSITY	0.81	0.12	DRZ_1:PRMX_LOG	0.86	-0.12
8	S_HALITE:COMP_RCK	0.83	-0.13	CASTILER:COMP_RCK	0.87	0.12
9	DRZ_PCS:PRMX_LOG	0.84	-0.12	WAS_AREA:BIOGENFC	0.88	0.11
10	WAS_AREA:SAT_RBRN	0.85	-0.10	S_HALITE:PRESSURE	0.89	-0.08
11	S_MB139:RELP_MOD	0.86	-0.09	SPALLMOD:REPIPOR	0.90	0.09
12				CULEBRA:MINP_FAC	0.91	0.08
13				SHFTU:SAT_RGAS	0.91	-0.08
14				S_HALITE:POROSITY	0.92	0.07
15				GLOBAL:TRANSIDX	0.92	0.07
16				PCS_T2:POR2PERM	0.92	0.06

Table 14 – Stepwise Ranked Regression Analysis for Mean DirectBrine Releases, Replicate 3 of the CRA14 and CRA19 Analyses

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative Rvalue with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

4.3.2.1 Direct Brine Volume Releases

Table 15 through Table 17 compare the parameters that showed significant correlations to mean direct brine volume releases between the CRA14 and CRA19 analyses based on a stepwise regression using ranked data. Results are similar to those for direct brine releases, with the expected exception that the SOLMOD3:SOLVAR parameter is not impactful to the variability in DBR volumes. As seen for DBRs, the CASTILER:PRESSURE (20 % control across all three replicates), STEEL:CORRMCO2 (10-16 %), and GLOBAL:PBRINE (4-15 %) parameters are impactful on the variability. Additionally, the BH_SAND:PRMX_LOG parameter (the (logarithm of the) permeability of the silty-sand-filled borehole) shows a relatively high level of control on the variability of DBR volumes (9-24 %). The WAS_AREA:SAT_RBRN parameter is impactful at a 4-6 % level for the CRA19 analysis, increased from 0-4 % for the CRA14 analysis.

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The new GLOBAL:GDEPFAC parameter (energy deposition probability for wetted solid radionuclides) distribution, which plays a role in radiolytic gas generation, shows no impact on the variability of DBR volumes for any of the three replicates (Figure 8).

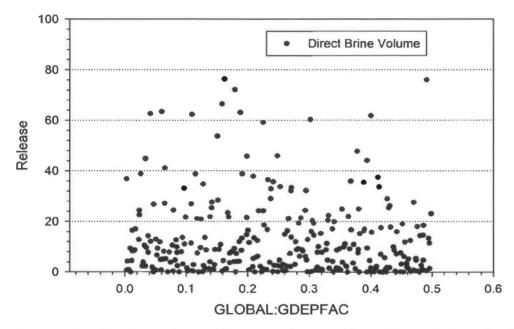


Figure 8 – Scatterplot of Energy Deposition Probability for Wetted Solid Radionuclides Versus Mean Direct Brine Release Volumes for the CRA19 Analysis



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Table 15 – Stepwise Ranked Regression Analysis for Mean Direct Brine Volumes, Replicate 1 of the CRA14 and CRA19 Analyses

	CRA14 Replie		CRA19 Replicate 1			
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC
1	CASTILER:PRESSURE	0.26	0.51	CASTILER:PRESSURE	0.20	0.46
2	BH_SAND:PRMX_LOG	0.44	-0.44	BH_SAND:PRMX_LOG	0.35	-0.38
3	S_HALITE:POROSITY	0.55	0.29	STEEL:CORRMCO2	0.46	-0.33
4	WAS_AREA:PROBDEG	0.60	0.25	WAS_AREA:SAT_RBRN	0.52	-0.22
5	WAS_AREA:BIOGENFC	0.65	0.22	GLOBAL:PBRINE	0.56	0.21
6	S_MB139:RELP_MOD	0.67	-0.19	SHFTL_T2:PRMX_LOG	0.58	0.14
7	DRZ_PCS:PRMX_LOG	0.70	-0.15			
8	S_HALITE:COMP_RCK	0.71	-0.12			

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

Table 16 – Stepwise Ranked Regression Analysis for Mean Direct Brine Volumes, Replicate 2 of the CRA14 and CRA19 Analyses

	CRA14 Replie	cate 2		CRA19 Replic	ate 2	
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC
1	BH_SAND:PRMX_LOG	0.29	-0.52	CASTILER:PRESSURE	0.20	0.43
2	CASTILER:PRESSURE	0.48	0.45	STEEL:CORRMCO2	0.36	-0.40
3	S_HALITE:POROSITY	0.56	0.28	GLOBAL:PBRINE	0.51	0.40
4	GLOBAL:PBRINE	0.59	0.19	BH_SAND:PRMX_LOG	0.60	-0.29
5	WAS_AREA:BIOGENFC	0.62	0.18	WAS_AREA:SAT_RBRN	0.64	-0.20
6	CASTILER:COMP_RCK	0.64	0.14	WAS_AREA:GRATMICI	0.66	-0.15
7	GLOBAL:OXSTAT	0.65	-0.13	CASTILER:COMP_RCK	0.68	0.16
8				S_HALITE:POROSITY	0.70	0.15
9				DRZ_PCS:PRMX_LOG	0.71	0.12
10				SHFTU:SAT_RBRN	0.73	-0.12
11				WAS_AREA:BRUCITEH	0.74	-0.11

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^CCumulative Rvalue with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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	CRA14 Replicate 3			CRA19 Replicate 3				
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC		
1	CASTILER:PRESSURE	0.35	0.63	BH_SAND:PRMX_LOG	0.24	-0.51		
2	BH_SAND:PRMX_LOG	0.57	-0.47	CASTILER:PRESSURE	0.44	0.46		
3	DRZ_1:PRMX_LOG	0.65	-0.25	GLOBAL:PBRINE	0.56	0.34		
4	WAS_AREA:SAT_RBRN	0.69	-0.19	STEEL:CORRMCO2	0.66	-0.33		
5	GLOBAL:PBRINE	0.72	0.19	WAS_AREA:SAT_RBRN	0.72	-0.25		
6	GLOBAL:CLIMTIDX	0.75	0.16	DRZ_1:PRMX_LOG	0.74	-0.14		
7	S_HALITE:POROSITY	0.77	0.16	GLOBAL:CLIMTIDX	0.76	0.11		
8	DRZ_PCS:PRMX_LOG	0.79	-0.14	WAS_AREA:BIOGENFC	0.77	0.11		
9	WAS_AREA:PROBDEG	0.81	0.13					
10	S_MB139:PRMX_LOG	0.82	0.11					
11	(Composite):OXSTAT	0.83	-0.10					
12	SOLMOD4:SOLVAR	0.84	0.09					

Table 17 – Stepwise Ranked Regression Analysis for Mean DirectBrine Volumes, Replicate 3 of the CRA14 and CRA19 Analyses

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

4.4 Culebra Releases

Releases from the Culebra are releases of contaminated brine originating in the repository and which are later transported to the Culebra and eventually to the Land Withdrawal Boundary (LWB). The release of radionuclides from the Culebra starts with the transport of the radionuclides from the waste area to the Culebra. A regression analysis on the non-zero data shows that the logarithms of these two releases are well correlated although the scatter of residuals is still quite large ($R^2 = 0.53$, Figure 9).



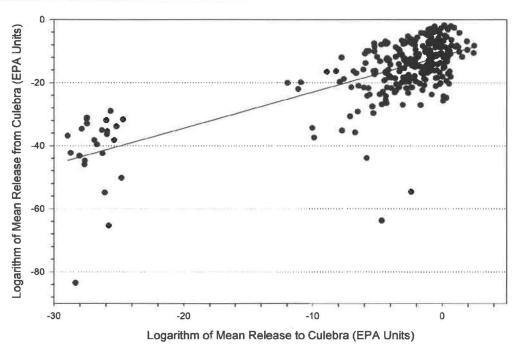


Figure 9 – Correlation Between Releases to and from the Culebra

4.4.1 Changes in Releases Since the CRA14 Analysis

Releases from the Culebra for CRA19 analysis show an overall increase across all probabilities compared to those of the CRA14 analysis (Brunell 2019). The releases are a product of releases to the Culebra, which are influenced by radionuclide concentrations in brine and brine flows to the Culebra. Radionuclide concentrations in brine have decreased in general (Sarathi 2019) and brine flows to the Culebra are mixed (Day 2019). Releases to the Culebra, on a CCDF basis, are not much changed (Brunell 2019). However, while CCDFs of releases from the Culebra are increased, releases on a vector basis (i.e., averaged across futures) vary drastically between the CRA14 and CRA19 analyses (Figure 10).

As observed by Kirchner (2013), the curve of mean probabilities as the release level increases is influenced more and more by the shape of the CCDF curves for individual vectors that remain above zero until only one vector controls the shape of the mean value curve. In other words, the sensitivity analysis shows the impact of parameters on the mean of the distributions associated with each vector but about many of those curves terminate (go to zero) at release below 0.0001 EPA units and hence the sensitivity analysis may do little to help explain the behavior of the curve for mean probability of release from the Culebra.

The low number of substantial releases from the Culebra undoubtedly play a role in the observed variability of releases. Across replicates, the number of vectors having releases from the Culebra in the CRA19 analysis that exceeded 0.0001 was greater than that from the CRA14 analysis (Table 3), but only marginally. The releases of zero are due, for the most part, to transport rates frequently being too small to enable contaminants to reach the boundary within the simulation

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period, 10,000 years. The times of the intrusions giving rise to flows *to* the Culebra are also likely to influence whether or not such releases occur. These times are not represented in the "sampled" input parameters and thus cannot be associated with the releases in a sensitivity analysis. Changes in the releases from the Culebra are due in part to changes in the rate of transport because the flow fields used in the CRA19 analysis are slightly different from those used in the CRA14 analysis (rerun as part of the code migration to the Solaris system (Kirchner et al. 2014)). However, there were no changes in the matrix distribution coefficients (K_d) for the radionuclides, so there was no change in the releases whereas previously that had none because of having earlier intrusion times in some futures, thus providing the time needed to have the radionuclides reach the LWB.

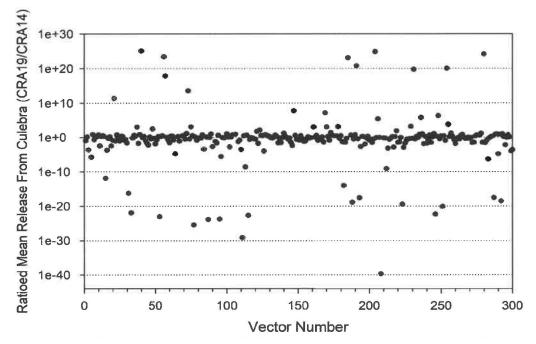


Figure 10 – Comparison of Ratioed Mean Release from the Culebra for the CRA14 and CRA19 Analyses on a Vector Basis

4.4.2 Regression Analysis Results

Table 18 through Table 20 compare the parameters that showed significant correlations to mean releases from the Culebra for the CRA14 and CRA19 analyses based on a stepwise regression using ranked data. Table 21 through Table 23 compare the parameters that showed significant correlations to mean releases to the Culebra between the CRA14 and CRA19 analyses based on a stepwise regression using ranked data. The number of nonzero mean releases from the Culebra (Table 3 and Table 4) has slightly increased, and the number of vectors with mean releases above the 0.0001 EPA Unit threshold is still very small. A large number of small values may reduce

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the effectiveness of the regression analysis, as they may tend to negate the assumption of linear regression that errors (residuals) are normally distributed.

The dominant parameter with regard to controlling releases both *to* the Culebra and *from* the Culebra in the CRA19 analysis is the BH_SAND:PRMX_LOG parameter (the (logarithm of) intrinsic permeability in the X-direction for a sand-filled borehole). Conceptually, the flow of brine up the borehole (and thus to the Culebra) should be positively influenced by increasing values for BH_SAND:PRMX_LOG (Stein and Zelinski 2003). This parameter accounts for 28-45 % of the variability in releases *from* the Culebra and 79-81 % of the releases *to* the Culebra across the three replicates of the CRA19 analysis.

Variability is observed in the other "dominant" parameters among the three replicates. The (Composite):MKD_U parameter (composite variable for uranium matrix partition coefficient) is the second highest parameter in replicates 1 and 3 (16-17 %), but completely absent from replicate 2. Similarly, the (Composite):OXSTAT parameter has up to 12 % control in replicate 2, but is absent from replicate 3. Similarly, the CULEBRA:APOROS parameter (advective porosity in the Culebra) shows an impact of 5-7 % in two replicates, but is absent in the third.

Although SOLMOD3:SOLVAR is ranked second in all three replicates of the releases to the Culebra, it does not appear for any replicates in releases from the Culebra—it is therefore somewhat impactful on the variability of the radionuclides that reach the Culebra (3-7 %), but not in releases from the Culebra.



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Table 18 – Stepwise Ranked Regression Analysis for Mean Releases from the Culebra, Replicate 1 of the CRA14 and CRA19 Analyses

	CRA14 Replic	cate 1		CRA19 Replic	ate 1	
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC
1	(Composite):MKD_U	0.34	-0.52	BH_SAND:PRMX_LOG	0.28	0.49
2	BH_SAND:PRMX_LOG	0.55	0.46	(Composite):MKD_U	0.45	-0.21
3	CULEBRA: APOROS	0.59	-0.19	CULEBRA: APOROS	0.50	-0.20
4	GLOBAL:CLIMTIDX	0.61	0.15	S_HALITE:COMP_RCK	0.54	0.21
5	CULEBRA:HMBLKLT	0.63	0.15	DRZ_PCS:PRMX_LOG	0.56	0.18
6	WAS_AREA:SAT_WICK	0.65	0.14	GLOBAL:GDEPFAC	0.59	-0.15
7	SOLMOD3:SOLVAR	0.67	0.15	(Composite):OXSTAT	0.61	0.24
8	(Composite):MKD_PU	0.69	-0.13	CULEBRA:HMBLKLT	0.63	0.15
9	SPALLMOD:REPIPERM	0.71	-0.12	GLOBAL:CLIMTIDX	0.65	0.15
10				S_HALITE:POROSITY	0.67	-0.14
11				WAS_AREA:BRUCITEC	0.69	0.14
12				STEEL:HUMCORR	0.70	-0.12

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^CCumulative Rvalue with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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Table 19 – Stepwise Ranked Regression Analysis for Mean Releases from the Culebra, Replicate 2 of the CRA14 and CRA19 Analyses

	CRA14 Replie		CRA19 Replicate 2				
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC	
1	BH_SAND:PRMX_LOG	0.41	0.60	BH_SAND:PRMX_LOG	0.45	0.66	
2	GLOBAL:OXSTAT	0.59	0.27	GLOBAL:OXSTAT	0.57	0.35	
3	(Composite):MKD_U	0.63	-0.26	CULEBRA:MINP_FAC	0.62	-0.21	
4	CULEBRA:MINP_FAC	0.67	-0.19	WAS_AREA:BIOGENFC	0.65	-0.16	
5	CULEBRA:HMBLKLT	0.69	0.16	WAS_AREA:SAT_RBRN	0.67	0.16	
6	CULEBRA: APOROS	0.71	-0.15	STEEL:CORRMCO2	0.69	-0.14	
7	WAS_AREA:GRATMICH	0.73	-0.12	CONC_PLG:PRMX_LOG	0.70	-0.11	
8	PHUMOX3:PHUMCIM	0.74	0.12				

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

Table 20 – Stepwise Ranked Regression Analysis for Mean Releases from the Culebra, Replicate 3 of the CRA14 and CRA19 Analyses

	CRA14 Replie	cate 3		CRA19 Replicate 3			
Step ^a	Variable ^b	R ^{2c} SRRC		Variable	R ²	SRRC	
1	BH_SAND:PRMX_LOG	0.26	0.49	BH_SAND:PRMX_LOG	0.26	0.49	
2	(Composite):MKD_U	0.47	-0.45	(Composite):MKD_U	0.42	-0.36	
3	CULEBRA: APOROS	0.60	-0.36	CULEBRA: APOROS	0.49	-0.28	
4	PCS_T1:POROSITY	0.61	0.13	CASTILER:PRESSURE	0.53	0.19	
5				SOLMOD4:SOLVAR	0.56	0.14	
6				S_MB139:PRMX_LOG	0.58	-0.17	
7				GLOBAL:CLIMTIDX	0.61	0.15	
8				S_MB139:SAT_RBRN	0.62	-0.13	

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^C Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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Table 21 – Stepwise Ranked Regression Analysis for Mean Releases to Culebra, Replicate 1 of the CRA14 and CRA19 Analyses

	CRA14 Replic	cate 1		CRA19 Replicate 1				
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC		
1	BH_SAND:PRMX_LOG	0.85	0.92	BH_SAND:PRMX_LOG	0.79	0.89		
2	SOLMOD3:SOLVAR	0.90	0.24	SOLMOD3:SOLVAR	0.82	0.16		
3	CASTILER:PRESSURE	0.91	0.09	CASTILER:PRESSURE	0.84	0.17		
4	WAS_AREA:PROBDEG	0.91	0.08	S_HALITE:COMP_RCK	0.87	0.15		
5	DRZ_1:PRMX_LOG	0.92	-0.08	STEEL:CORRMCO2	0.88	-0.12		
6	CASTILER:PRMX_LOG	0.92	-0.07	DRZ_PCS:PRMX_LOG	0.89	0.09		
7	DRZ_PCS:PRMX_LOG	0.93	0.06	WAS_AREA:SAT_RBRN	0.90	-0.09		
8	(Composite):MKD_PU	0.93	-0.07	S_HALITE:PRESSURE	0.90	0.08		
9	STEEL:CORRMCO2	0.93	-0.06	SHFTU:SAT_RGAS	0.91	0.07		
10	SHFTL_T1:PRMX_LOG	0.94	0.06	PCS_T1:PORE_DIS	0.91	0.07		

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^C Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

Table 22 – Stepwise Ranked Regression Analysis for Mean Releases to Culebra, Replicate 2 of the CRA14 and CRA19 Analyses

	CRA14 Replie		CRA19 Replicate 2				
Step ^a	Variable ^b	R ^{2c}	SRRC₫	Variable	R ²	SRRC	
1	BH_SAND:PRMX_LOG	0.84	0.92	BH_SAND:PRMX_LOG	0.79	0.91	
2	SOLMOD3:SOLVAR	0.88	0.23	SOLMOD3:SOLVAR	0.86	0.26	
3	CASTILER:PRESSURE	0.90	0.12	GLOBAL:PBRINE	0.87	0.12	
4	(Composite):OXSTAT	0.90	0.10	CASTILER:PRESSURE	0.88	0.10	
5	S_MB139:RELP_MOD	0.91	-0.08	CULEBRA:DPOROS	0.89	-0.09	
6	SHFTU:SAT_RGAS	0.91	-0.07	STEEL:CORRMCO2	0.89	-0.08	
7	PHUMOX3:PHUMCIM	0.92	0.06	S_HALITE:COMP_RCK	0.90	0.07	
8				WAS_AREA:BIOGENFC	0.90	-0.07	

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative Rvalue with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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Table 23 – Stepwise Ranked Regression Analysis for Mean Releases to Culebra, Replicate 3 of the CRA14 and CRA19 Analyses

	CRA14 Replic	cate 3		CRA19 Replicate 3				
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC		
1	BH SAND:PRMX LOG	0.85	0.93	BH_SAND:PRMX_LOG	0.81	0.90		
2	SOLMOD3:SOLVAR	0.89	0.19	SOLMOD3:SOLVAR	0.84	0.16		
3	GLOBAL:OXSTAT	0.90	0.12	S_HALITE:POROSITY	0.86	-0.16		
4	CASTILER:PRESSURE	0.91	0.09	CASTILER:PRESSURE	0.88	0.13		
5	WAS_AREA:BRUCITEC	0.92	-0.09	WAS_AREA:SAT_RGAS	0.89	0.08		
6	SOLMOD4:SOLVAR	0.93	0.07	STEEL:CORRMCO2	0.90	-0.08		
7	CULEBRA:MINP_FAC	0.93	0.07	CULEBRA: APOROS	0.90	-0.08		
8	SHFTU:SAT_RBRN	0.93	-0.07	S_MB139:SAT_RBRN	0.91	-0.07		
9	CASTILER:PRMX_LOG	0.94	0.06					
10	CULEBRA: APOROS	0.94	-0.06					
11	SPALLMOD:REPIPERM	0.94	-0.05					

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative Rvalue with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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4.5 Total Releases

Total releases are the sum of cuttings and cavings and spallings releases, DBRs, and releases from the Culebra.

4.5.1 Changes in Releases Since the CRA14 Analysis

As releases increased for all release mechanisms at all probabilities, total releases also increased at all probabilities (Brunell 2019). As in the CRA14 analysis, cuttings and cavings releases and direct brine releases dominate the total releases estimated in the CRA19 analysis. Spallings releases have increased substantially to be almost on par with DBRs. Releases from the Culebra continue to contribute little to total releases.

4.5.2 Regression Analysis Results

Table 24 through Table 26 compare the parameters that showed significant correlations to mean total releases between the CRA14 and CRA19 analyses based on a stepwise regression using ranked data. Across the three replicates of the CRA19 analysis, 56 % to 74 % of the variability is accounted for in the regression model containing the largest number of variables. The number of contributors of at least 5 % has increased across all three replicates and the top contributor in each replicate has decreased in influence across all replicates—these are indicative of the increased relative importance of DBRs compared to cuttings and cavings releases for the CRA19 analysis.

Whereas for the CRA14 analysis the BOREHOLE:TAUFAIL parameter (waste shear strength) was the most dominant parameter with regard to controlling total releases in all three replicates, the SOLMOD3:SOLVAR parameter (solubility multiplier for III oxidation states) is now the most dominant parameter contributing to variability in total releases in all three replicates (tied with parameter BH_SAND:PRMX_LOG in replicate 3). In the CRA14 analysis, it contributed 11-15 % of control, while in the CRA19 analysis, it contributed 17-23 %. An update of the prediction error of the EQ3/6 model using data relevant to conditions in the WIPP repository decreased the distribution range for the SOLMOD3:SOLVAR parameter as compared to the CRA14 analysis (Domski 2019). The SOLMOD3:SOLVAR parameter is defined by a cumulative distribution. The lower bound was increased from -3.5 to about -1.1 and the upper bound stayed the same at about 3.0, so the distribution range was reduced by 2.4.

The BOREHOLE: TAUFAIL parameter is now the second-most dominant parameter in two of three replicates and the third-most dominant parameter in the third replicate. It has decreased in control from 30-43 % for the CRA14 analysis to 11-15 % for the CRA19 analysis.

The BH_SAND:PRMX_LOG parameter has increased in dominance from 0-3 % control in the CRA14 analysis to 6-17 % control in the CRA19 analysis. It is also shown above to impact the variability in DBR volumes and releases to/from the Culebra, but not DBRs.

The updated parameter distribution for the GLOBAL:PBRINE parameter (probability that a drilling intrusion penetrates the pressurized brine in the Castile) has increased in importance

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from 0-1 % control in the CRA14 analysis to 0-8 % control in the CRA19 analysis (absent from replicate 1).

The CASTILER:PRESSURE parameter (initial brine pore pressure in the Castile) remains one of the top contributing parameters with 6-9 % control across the three replicates.

Table 24 – Stepwise Ranked Regression Analysis for Mean TotalReleases, Replicate 1 of the CRA14 and CRA19 Analyses

	CRA14 Replie	cate 1		CRA19 Replicate 1				
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC		
1 BOREHOLE:TAUFAIL		0.30	-0.55	SOLMOD3:SOLVAR	0.23	0.51		
2	SOLMOD3:SOLVAR	0.43	0.37	BOREHOLE:TAUFAIL	0.35	-0.35		
3	CASTILER:PRESSURE	0.52	0.28	CASTILER:PRESSURE	0.44	0.31		
4	S_HALITE:PRMX_LOG	0.56	0.19	BH_SAND:PRMX_LOG	0.50	-0.27		
5	WAS_AREA:PROBDEG	0.58	0.13	STEEL:CORRMCO2	0.53	-0.19		
6	SHFTU:SAT_RGAS	0.61	-0.15	WAS_AREA:PROBDEG	0.56	0.17		
7	S_HALITE:POROSITY	0.63	0.15					
8	BOREHOLE:DOMEGA	0.65	0.13					

^a Steps in stepwise regression analysis

^b Variables listed in order of selection



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^c Cumulative Rvalue with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

Table 25 – Stepwise Ranked Regression Analysis for Mean TotalReleases, Replicate 2 of the CRA14 and CRA19 Analyses

	CRA14 Replie	cate 2		CRA19 Replicate 2				
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC		
1	BOREHOLE:TAUFAIL	0.43	-0.64	SOLMOD3:SOLVAR	0.23	0.48		
2	SOLMOD3:SOLVAR	0.58	0.39	BOREHOLE:TAUFAIL	0.38	-0.40		
3	CASTILER:PRESSURE	0.62	0.25	CASTILER:PRESSURE	0.47	0.28		
4	S_HALITE:POROSITY	0.65	0.17	GLOBAL:PBRINE	0.54	0.28		
5	WAS_AREA:PROBDEG	0.67	0.18	BH_SAND:PRMX_LOG	0.62	-0.27		
6	(Composite):MKD_U	0.69	-0.14	S_HALITE:POROSITY	0.65	0.19		
7	BOREHOLE:DOMEGA	0.71	0.14	SHFTU:SAT_RGAS	0.67	-0.12		
8	BH_SAND:PRMX_LOG	0.72	-0.11	STEEL:CORRMCO2	0.68	-0.12		
9	GLOBAL:PBRINE	0.73	0.11					
10	PCS_T1:PORE_DIS	0.75	-0.12					
11	SPALLMOD:REPIPOR	0.76	0.11					
12	CULEBRA:MINP_FAC	0.77	-0.11					

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

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^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

Table 26 – Stepwise Ranked Regression Analysis for Mean TotalReleases, Replicate 3 of the CRA14 and CRA19 Analyses

	CRA14 Repli	cate 3		CRA19 Replicate 3			
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC	
1	BOREHOLE:TAUFAIL	0.32	-0.55	BH_SAND:PRMX_LOG	0.17	-0.39	
2	SOLMOD3:SOLVAR	0.43	0.32	SOLMOD3:SOLVAR	0.34	0.39	
3	GLOBAL:OXSTAT	0.49	0.25	BOREHOLE:TAUFAIL	0.45	-0.34	
4	CASTILER:PRESSURE	0.53	0.19	GLOBAL:PBRINE	0.53	0.28	
5	BOREHOLE:DOMEGA	0.56	0.20	CASTILER:PRESSURE	0.59	0.24	
6	BH_SAND:PRMX_LOG	0.59	-0.18	DRZ_1:PRMX_LOG	0.62	-0.19	
7	CULEBRA: APOROS	0.62	0.16	SPALLMOD:PARTDIAM	0.64	-0.17	
8	S_HALITE:POROSITY	0.64	0.15	CASTILER:COMP_RCK	0.67	0.13	
9				S_HALITE:PRESSURE	0.69	-0.14	
10				CULEBRA:MINP_FAC	0.70	0.13	
11				S_MB139:RELP_MOD	0.72	-0.15	
12				WAS_AREA:SAT_RBRN	0.74	-0.13	

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R² value with entry of each variable into regression model ^d Star

^d Standardized Rank Regression Coefficient

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5.0 SUMMARY

Parameter and model changes between the CRA14 and CRA19 analyses have contributed to changes in calculated releases. Two new sampled parameters have been added and one subtracted, for a total of 64 sampled parameters that could potentially contribute to the variability in releases across the 100 vectors in each of three replicates. The sensitivity of each individual release mechanism, as well as total releases, to sampled parameters has been analyzed using a stepwise linear multiple regression analysis.

Releases have increased for total releases, as well as all individual release mechanisms, at all probabilities from the CRA14 analysis to the CRA19 analysis. As in the CRA14 analysis, cuttings and cavings releases and direct brine releases dominate the total releases calculated in the CRA19 analysis. Spallings releases have increased substantially to be almost on par with DBRs. Releases from the Culebra continue to contribute little to total releases.

Whereas for the CRA14 analysis the BOREHOLE:TAUFAIL parameter (waste shear strength) was the most dominant parameter with regard to controlling total releases in all three replicates, the SOLMOD3:SOLVAR parameter (solubility multiplier for III oxidation states) is now the most dominant parameter contributing to variability in total releases in all three replicates (tied with parameter BH_SAND:PRMX_LOG in replicate 3). The increased importance is due in part to the shifting of the distribution mean to a higher value (thus making it more impactive on DBRs), as well as in part to the increased contribution of DBRs to total releases. Nonzero DBR volumes have also increased, such that some intrusions that previously had zero DBRs (and thus zero contribution of the SOLMOD3:SOLVAR parameter to DBRs) now have nonzero DBRs.

The BOREHOLE: TAUFAIL parameter is now the second-most dominant parameter for total releases. It has decreased in importance, not due to the minor change in assigned distribution, but to the increased impact of the variability in waste stream concentrations.

The BH_SAND:PRMX_LOG parameter has increased in importance in the CRA19 analysis due to the impact on DBRs. The CASTILER:PRESSURE parameter continues to be one of the more important parameters in terms of variability in total releases, due to its impact on DBRs.

The updated distribution for the STEEL:CORRMCO2 parameter has led to increased importance in the variability of DBRs, but the correlation with DBRs is negative—increased gas generation rates associated with this parameter lead to decreased DBRs due to the impact of repository pressure to reduce waste area saturations.

The influence of the GLOBAL:PBRINE parameter on DBRs was somewhat increased in comparison to the CRA14 due to the change in assigned distribution and increased impact of DBRs on total releases.

Of the other sampled parameters that were changed or were new since the CRA14, none had any substantial impact on releases. The change in the distribution of SOLMOD4:SOLVAR had little impact on DBR or releases from the Culebra. The GLOBAL:GDEPFAC, STEEL:HUMCORR, and WAS_AREA:HYMAGCON parameters did not show much (or only very weak) correlations with releases from the repository.

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6.0 REFERENCES

Bethune, J. 2019. Analysis Package for Direct Brine Releases in the 2019 Compliance Recertification Application Performance Assessment (CRA-2019 PA). Sandia National Laboratories, Carlsbad, NM. ERMS 571370.

Brunell, S. 2019. Analysis Package for Normalized Releases in the 2019 Compliance Recertification Application Performance Assessment (CRA-2019 PA). Sandia National Laboratories, Carlsbad, NM. ERMS 571373.

Clayton, D.J., S. Dunagan, J.W. Garner, A.E. Ismail, T.B. Kirchner, G.R. Kirkes, M.B. Nemer. 2008. Summary Report of the 2009 Compliance Recertification Application Performance Assessment. Sandia National Laboratories, Carlsbad, NM. ERMS 548862.

Clayton, D.J., R.C. Camphouse, J.W. Garner, A.E. Ismail, T.B. Kirchner, K.L. Kuhlman, M.B. Nemer. 2010. Summary Report of the CRA-2009 Performance Assessment Baseline Calculation. Sandia National Laboratories, Carlsbad, NM. ERMS 553039.

Cotsworth, E. 2005. EPA Letter on Conducting the Performance Assessment Baseline Change (PABC) Verification Test. U.S. EPA, Office of Radiation and Indoor Air, Washington, D.C. ERMS 538858.

Cotsworth, E. 2009. EPA Letter on CRA-2009 First Set of Completeness Comments. U.S. EPA, Office of Radiation and Indoor Air, Washington, D.C. ERMS 551444.

Domski, P.S. 2019. Uncertainty Analysis of Actinide Solubilities for CRA 2019. Sandia National Laboratories, Carlsbad, NM. ERMS 571179.

Kicker, D. 2019a. Analysis Package for Cuttings, Cavings, and Spallings in the 2019 Compliance Recertification Application Performance Assessment (CRA-2019 PA). Sandia National Laboratories, Carlsbad, NM. ERMS 571369.

Kicker, D. 2019b. Analysis Package for Inventory EPA Units in the 2019 Compliance Recertification Application Performance Assessment (CRA-2019 PA). Sandia National Laboratories, Carlsbad, NM. ERMS 571372.

Kicker, D.C., C. Herrick, and T. Zeitler. 2015. Impact of the DRSPALL Modification on Waste Isolation Pilot Plant Performance Assessment Calculations. Sandia National Laboratories, Carlsbad, NM. ERMS 564863.

Kim, S. and L. Feng. 2019. Input Parameter Report for the 2019 Compliance Recertification Application Performance Assessment (CRA-2019 PA), Rev. 1. Sandia National Laboratories, Carlsbad, NM. ERMS 571660.

Kirchner, T. 2004a. "Stepwise regression analysis of the final release for each release mechanism, in response to C-23-18, Revision 2." Memorandum to David Kessel dated December 6, 2004. Sandia National Laboratories. Carlsbad, NM. ERMS 537992.

Kirchner, T. 2004b. CRA Response Activity, Tracking Number 09/02/04Q, DOE Response to Comment C-23-18, Revision 1, ERMS 538114.



Rev. 0, ERMS 571374

Kirchner, T. 2012. AP-162 Revision 0: Analysis Plan for the Migration of the Performance Assessment Codes to the Sun Solaris Blade Server Running with Intel Processors. Sandia National Laboratories, Carlsbad, NM. ERMS 557765.

Kirchner, T. 2013. Sensitivity of the CRA-2014 Performance Assessment Releases to Parameters. Sandia National Laboratories, Carlsbad, NM. ERMS 560043.

Kirchner, T., A. Gilkey, and J. Long. 2014. Summary Report on the Migration of the WIPP PA Codes from VMS to Solaris, AP-162 Revision 1. Sandia National Laboratories, Carlsbad, NM. ERMS 561757.

Kirchner, T., A. Gilkey, and J. Long. 2015. Addendum to the Summary Report on the Migration of the WIPP PA Codes from VMS to Solaris, AP-162. Sandia National Laboratories, Carlsbad, NM. ERMS 564675.

Leigh, C.D., J.F. Kanney, L.H. Brush, J.W. Garner, G.R. Kirkes, T. Lowry, M.B. Nemer, J.S. Stein, E.D. Vugrin, S. Wagner, and T.B. Kirchner. 2005. 2004 Compliance Recertification Application Performance Assessment Baseline Calculation, Revision 0. Sandia National Laboratories, Carlsbad, NM. ERMS 541521.

Long, J. 2013. Execution of Performance Assessment Codes for the CRA-2014 Performance Assessment. Sandia National Laboratories, Carlsbad, NM. ERMS 560016.

Long, J. 2019. Computational Code Execution and File Management for the 2019 Compliance Recertification Application Performance Assessment (CRA-2019 PA). Sandia National Laboratories, Carlsbad, NM. ERMS 571375.

MacKinnon, R.J., and G. Freeze. 1997a. Summary of EPA-Mandated Performance Assessment Verification Test (Replicate 1) and Comparison With the Compliance Certification Application Calculations, Revision 1. Sandia National Laboratories, Carlsbad, NM. ERMS 422595.

MacKinnon, R.J., and G. Freeze. 1997b. Summary of Uncertainty and Sensitivity Analysis Results for the EPA-Mandated Performance Assessment Verification Test, Rev. 1. Sandia National Laboratories, Carlsbad, NM. ERMS 420669.

MacKinnon, R.J., and G. Freeze. 1997c. Supplemental Summary of EPA-Mandated Performance Assessment Verification Test (All Replicates) and Comparison With the Compliance Certification Application Calculations, Revision 1. Sandia National Laboratories, Carlsbad, NM. ERMS 414880.

Sarathi, R. 2019. Analysis Package for Actinide Mobilization and Salado Transport in the 2019 Compliance Recertification Application Performance Assessment (CRA-2019 PA). Sandia National Laboratories, Carlsbad, NM. ERMS 571371.

Stein, J. S., and W. Zelinski. 2003. Analysis Package for BRAGFLO: Compliance Recertification Application. Analysis Report. Sandia National Laboratories, Carlsbad, NM. ERMS 530163.

U.S. Congress. 1992. WIPP Land Withdrawal Act, Public Law 102-579, 106 Stat. 4777, 1992; as amended by Public Law 104-201, 110 Stat. 2422, 1996.

Rev. 0, ERMS 571374

U.S. Department of Energy (DOE) 1996. Title 40 CFR Part 191 Compliance Certification Application for the Waste Isolation Pilot. U.S. Department of Energy Waste Isolation Pilot Plant, Carlsbad Area Office, Carlsbad, NM. DOE/CAO-1996-2184.

U.S. Department of Energy (DOE) 2004. Title 40 CFR Part 191 Compliance Recertification Application for the Waste Isolation Pilot Plant, , 10 vols., U.S. Department of Energy Waste Isolation Pilot Plant, Carlsbad Area Office, Carlsbad, NM. DOE/WIPP 2004-3231.

U.S. Environmental Protection Agency (EPA). 1998. 40 CFR 194, Criteria for the Certification and Recertification of the Waste Isolation Pilot Plant's Compliance with the Disposal Regulations: Certification Decision: Final Rule, Federal Register. Vol. 63, 27354-27406.

U. S. Environmental Protection Agency (EPA). 2004. "EPA's Completeness Comments, 3rd Set." Letter from Elizabeth Cotsworth to Dr. R. Paul Detwiler. September 2, 2004. ERMS 536771.

U.S. Environmental Protection Agency (EPA). 2006. 40 CFR 194, Criteria for the Certification and Recertification of the Waste Isolation Pilot Plant's Compliance with the Disposal Regulations: Certification Decision: Final Rule, Federal Register. Vol. 71, 18010-18021.

U.S. Environmental Protection Agency (EPA). 2010. 40 CFR Part 194 Criteria for the Certification and Recertification of the Waste Isolation Pilot Plant's Compliance With the Disposal Regulations: Recertification Decision, Federal Register No. 222, Vol. 75, pp. 70584-70595, November 18, 2010.

U.S. Environmental Protection Agency (EPA). 2017. Criteria for the Certification and Recertification of the Waste Isolation Pilot Plant's Compliance with the Disposal Regulations; Recertification Decision. July 19, 2017. Office of Radiation and Indoor Air, Docket EPA-HQ-OAR-2014-0609-0079.

Zeitler, T.R, B. Day, J. Bethune, R. Sarathi, J. Long. 2017. Assessment of Abandoned Panel Closures in South End of Repository and Lack of Waste Emplacement in Panel 9. Sandia National Laboratories. Carlsbad, NM. ERMS 568459.

Zeitler, T.R. 2019a. Analysis Plan for the 2019 WIPP Compliance Recertification Application Performance Assessment. Sandia National Laboratories, Carlsbad, NM. ERMS 571150.

Zeitler, T.R. 2019b. Analysis Package for Parameter Sampling in the 2019 Compliance Recertification Application Performance Assessment (CRA-2019 PA). Sandia National Laboratories, Carlsbad, NM. ERMS 571367.

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Appendix A. Additional Data for CRA14 Analysis

This Appendix contains data from a parameter sensitivity analysis for the CRA14 (Rev. 2) analysis for comparison with similar data from the CRA19 analysis. This data was not included as part of the CRA-2014 PA, as the CRA-2014 PA included only the CRA14 (Rev. 0) results, which were later updated following the migration of WIPP PA codes to the Solaris system (Kirchner et al. 2014), the use of CCDFGF v.7.0 (Kirchner et al. 2015), and an update to the DRSPALL code that corrected an internal error (Kicker et al. 2015).

Due to changes made between the CRA-2014 PA and the CRA14 (Rev. 2) analysis, there are some differences for the CRA14 parameter sensitivity analysis between those presented in Kirchner (2013) and those presented in the main text of this report. The migration of codes from the VMS system (on which the CRA-2014 PA calculations were run) to the Solaris system (on which the CRA14 (Rev. 2) analysis was run) included a rerun of the entire CRA14 analysis, but did not include a rerun of the STEPWISE code for a parameter sensitivity analysis. Therefore, the CRA14 results presented in this report for comparison with the CRA19 results are presented for the first time.

Results queries were run for the CRA14 (Rev. 2) analysis (hereafter CRA14 analysis) to show the percentage of vectors in each replicate with maximum and average releases exceeding 0 and 0.0001 for each release mechanism and total releases (see Appendix B for queries). Data for CRA14 in Table 27 and Table 28 correspond to data in Table 3 and Table 4 for the CRA19 analysis.

Polozeo Typo	Repl	Replicate 1		Replicate 2		Replicate 3	
Release Type	>0	≥0.0001	>0	≥0.0001	>0	≥0.0001	
Cuttings and Cavings	100	100	100	100	100	100	
Direct Brine	99	73	99	81	100	68	
Spallings	52	16	51	21	50	17	
Total	100	100	100	100	100	100	
Total From Culebra	98	6	97	8	98	6	
Total To Culebra	98	64	97	67	98	65	

 Table 27 – Percentage of Vectors With Maximum Release Exceeding 0

 and 0.0001 EPA Units for CRA14 Analysis

Table 28 – Percentage of Vectors With Mean Release Exceeding 0 and0.0001 EPA Units for CRA14 Analysis

Release Type	Replicate 1		Replicate 2		Replicate 3	
	>0	≥0.0001	>0	≥0.0001	>0	≥0.0001
Cuttings and Cavings	100	100	100	100	100	100

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Direct Brine	99	98	99	99	100	99
Spallings	52	51	51	49	50	46
Total	100	100	100	100	100	100
Total From Culebra	98	11	97	14	98	9
Total To Culebra	98	81	97	81	98	78

For the most part, differences between the results of the parameter sensitivity analysis for the CRA-2014 PA and CRA14 (Rev. 2) analysis are very small, but there were notable differences related to the spallings portion of the analysis due to the correction of an error in the DRSPALL code that resulted in increased spallings releases upon rerunning for the CRA14 (Rev. 2) analysis.

Table 29 through Table 31 compare results for the CRA-2014 PA and CRA14 (Rev. 2) parameter sensitivity analysis results related to spallings releases (to be clear, the CRA14 (Rev. 2) results in these tables are the same as the CRA14 results in tables in the main text). The primary difference between the two analyses is that the SPALLMOD:REPIPERM variable (waste permeability), which was not previously on the list of variables with significant impact (i.e., $\Delta R^2 < 0.01$), showed a ΔR^2 of 0.10 to 0.14 for the CRA14 (Rev. 2) analysis. Thus we can conclude that the DRSPALL code correction resulted in increased importance of the SPALLMOD:REPIPERM parameter in terms of the variability in spallings releases.

Table 29 – Stepwise Ranked Regression Analysis for Mean Spallings Releases, Replicate 1 of the CRA-2014 PA and CRA14 (Rev. 2) Analysis

	CRA-2014 PA Re	plicate	1	CRA14 (Rev. 2) Replicate 1				
Step ^a	Variable ^b	R ^{2c}	SRRC₫	Variable	R ²	SRRC		
1	SPALLMOD:PARTDIAM	0.11	-0.35	CASTILER:PRESSURE	0.13	0.37		
2	BH_SAND:PRMX_LOG	0.22	-0.33	SPALLMOD:PARTDIAM	0.24	-0.33		
3	CASTILER:PRESSURE	0.32	0.35	SPALLMOD:REPIPERM	0.34	0.32		
4	SPALLMOD:REPIPOR	0.36	-0.21	BH_SAND:PRMX_LOG	0.40	-0.25		
5	WAS_AREA:PROBDEG	0.40	0.21	S_HALITE:POROSITY	0.45	0.22		
6	PCS_T3:POROSITY	0.43	0.18	SPALLMOD:REPIPOR	0.48	-0.19		
7	WAS_AREA:BIOGENFC	0.45	0.18	WAS_AREA:PROBDEG	0.51	0.17		
8	S_MB139:RELP_MOD	0.48	-0.19	DRZ_PCS:PRMX_LOG	0.53	-0.16		
9	SHFTU:SAT_RGAS	0.51	0.16	(Composite):OXSTAT	0.55	-0.15		

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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Table 30 – Stepwise Ranked Regression Analysis for Mean Spallings Releases, Replicate 2 of the CRA-2014 PA and CRA14 (Rev. 2) Analysis

	CRA-2014 PA Re	2	CRA14 (Rev. 2) Replicate 2			
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC
1	CASTILER:PRESSURE	0.12	0.35	BH_SAND:PRMX_LOG	0.15	-0.40
2	BH_SAND:PRMX_LOG	0.22	-0.32	SPALLMOD:REPIPERM	0.29	0.36
3	SPALLMOD:PARTDIAM	0.26	-0.20	CASTILER:PRESSURE	0.40	0.34
4	S_HALITE:POROSITY	0.30	0.21	S_HALITE:POROSITY	0.47	0.28
5	WAS_AREA:SAT_WICK	0.33	0.20	WAS_AREA:SAT_WICK	0.51	0.18
6	WAS_AREA:BIOGENFC	0.36	0.18	WAS_AREA:BIOGENFC	0.54	0.17
7	BOREHOLE:DOMEGA	0.39	-0.17	SPALLMOD:PARTDIAM	0.56	-0.17
8				GLOBAL:PBRINE	0.59	0.17

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

Table 31 – Stepwise Ranked Regression Analysis for Mean Spallings Releases, Replicate 3 of the CRA-2014 PA and CRA14 (Rev. 2) Analysis

	CRA-2014 PA Re	plicate	3	CRA14 (Rev. 2) Replicate 3		
Step ^a	Variable ^b	R ^{2c}	SRRCd	Variable	R ²	SRRC
1	SPALLMOD:PARTDIAM	0.11	-0.29	CASTILER:PRESSURE	0.16	0.39
2	S_HALITE:POROSITY	0.21	0.32	SPALLMOD:PARTDIAM	0.29	-0.34
3	CASTILER:PRESSURE	0.28	0.28	SPALLMOD:REPIPERM	0.41	0.33
4	DRZ_PCS:PRMX_LOG	0.33	-0.22	S_HALITE:POROSITY	0.49	0.28
5	SPALLMOD: TENSLSTR	0.38	-0.21	DRZ_PCS:PRMX_LOG	0.52	-0.18
6	BH_SAND:PRMX_LOG	0.42	-0.22	PCS_T1:SAT_RBRN	0.55	-0.15
7	WAS_AREA:PROBDEG	0.45	0.17	GLOBAL:CLIMTIDX	0.57	0.15
8	SHFTU:PRMX_LOG	0.48	0.16	BH_SAND:PRMX_LOG	0.59	-0.14
				SPALLMOD:REPIPOR	0.61	-0.15
				PCS_T1:POROSITY	0.63	-0.14

^a Steps in stepwise regression analysis

^b Variables listed in order of selection

^c Cumulative R value with entry of each variable into regression model ^d Standardized Rank Regression Coefficient

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Appendix B. SQL Queries for Extracting Data from WIPP PA Results Database

This appendix contains the SQL queries used to extract data from the WIPP PA Results Database (PA_Results) to populate some tables in this report. Table 32 contains the queries for the CRA19 results shown in Table 3 and Table 4. Table 33 contains the queries for the CRA14 results shown in Table 27 and Table 28.

Table 32 – Queries Used to Obtain Data for CRA19 Results in Table 3 and Table 4

Max or Mean Release	Threshold (EPA Units)	Table Number	Query
Max	>0	Table 3	SELECT Analysis, Replicate, VarName, COUNT(PeakValue) FROM CCDF_Statistics WHERE ((Analysis = "CRA19") and (AnalysisRevision = 0) and (Replicate in (1,2,3)) and (PeakValue > 0.000) and (VarName in ("Cuttings and Cavings", "Spallings", "Direct Brine Volume", "Direct Brine", "Total From Culebra", "Total To Culebra", "Total"))) GROUP BY VarName, Replicate;
Max	>0.0001	Table 3	SELECT Analysis, Replicate, VarName, COUNT(PeakValue) FROM CCDF_Statistics WHERE ((Analysis = "CRA19") and (AnalysisRevision = 0) and (Replicate in (1,2,3)) and (PeakValue > 0.0001) and (VarName in ("Cuttings and Cavings", "Spallings", "Direct Brine Volume", "Direct Brine", "Total From Culebra", "Total To Culebra", "Total"))) GROUP BY VarName, Replicate;



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Max or Mean Release	Threshold (EPA Units)	Table Number	Query	
Mean	>0	Table 4	SELECT Analysis, Replicate, VarName, COUNT(MeanResult) FROM CCDF_Statistics WHERE ((Analysis = "CRA19") and (AnalysisRevision = 0) and (Replicate in (1,2,3)) and (MeanResult > 0.000) and (VarName in ("Cuttings and Cavings", "Spallings", "Direct Brine Volume", "Direct Brine", "Total From Culebra", "Total To Culebra", "Total"))) GROUP BY VarName, Replicate;	
Mean	>0.0001	Table 4	SELECT Analysis, Replicate, VarName, COUNT(MeanResult) FROM CCDF_Statistics WHERE ((Analysis = "CRA19") and (AnalysisRevision = 0) and (Replicate in (1,2,3)) and (MeanResult > 0.0001) and (VarName in ("Cuttings and Cavings", "Spallings", "Direct Brine Volume", "Direct Brine", "Total From Culebra", "Total To Culebra", "Total"))) GROUP BY VarName, Replicate;	

Table 33 – Queries Used to Obtain Data for CRA14 Results in Table 27 and Table 28

Max or Mean Release	Threshold (EPA Units)	Table Number	Query
Max	>0	Table 27	SELECT Analysis, Replicate, VarName, COUNT(PeakValue) FROM CCDF_Statistics WHERE ((Analysis = "CRA19") and (AnalysisRevision = 0) and (Replicate in (1,2,3)) and (PeakValue > 0.000) and (VarName in ("Cuttings and Cavings", "Spallings", "Direct Brine Volume", "Direct Brine", "Total From Culebra", "Total To Culebra", "Total"))) GROUP BY VarName, Replicate;

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Max or Mean Release	Threshold (EPA Units)	Table Number	Query
Max	>0.0001	Table 27	SELECT Analysis, Replicate, VarName, COUNT(PeakValue) FROM CCDF_Statistics WHERE ((Analysis = "CRA19") and (AnalysisRevision = 0) and (Replicate in (1,2,3)) and (PeakValue > 0.0001) and (VarName in ("Cuttings and Cavings", "Spallings", "Direct Brine Volume", "Direct Brine", "Total From Culebra", "Total To Culebra", "Total"))) GROUP BY VarName, Replicate;
Mean	>0	Table 28	SELECT Analysis, Replicate, VarName, COUNT(MeanResult) FROM CCDF_Statistics WHERE ((Analysis = "CRA19") and (AnalysisRevision = 0) and (Replicate in (1,2,3)) and (MeanResult > 0.000) and (VarName in ("Cuttings and Cavings", "Spallings", "Direct Brine Volume", "Direct Brine", "Total From Culebra", "Total To Culebra", "Total"))) GROUP BY VarName, Replicate;
Mean	>0.0001	Table 28	SELECT Analysis, Replicate, VarName, COUNT(MeanResult) FROM CCDF_Statistics WHERE ((Analysis = "CRA19") and (AnalysisRevision = 0) and (Replicate in (1,2,3)) and (MeanResult > 0.0001) and (VarName in ("Cuttings and Cavings", "Spallings", "Direct Brine Volume", "Direct Brine", "Total From Culebra", "Total To Culebra", "Total"))) GROUP BY VarName, Replicate;

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