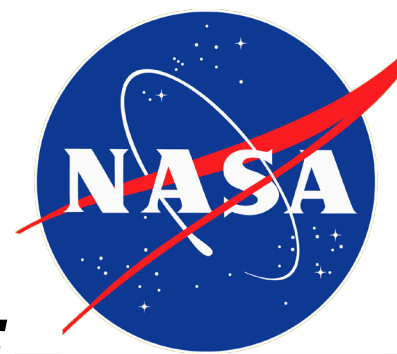


Under-Constrained SEE Data: Implications for Estimating and Bounding SEE Rates

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Abstract—Increasingly scarce SEE testing resources and rapid growth of the New Space sector have increased the prevalence of under-constrained SEE data. We develop Monte Carlo tools to assess implications for SEE

Intro: Problem of Ill-Constrained Data

Although many authors have provided guidance for optimizing SEE data[1-7], ill-constrained SEE data are becoming more common due to a variety of factors:

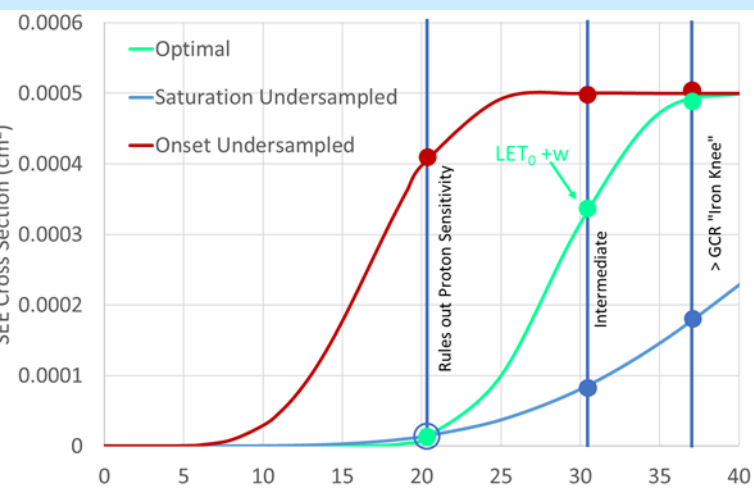


Fig. 1. 3-LET σ curve: If LETs too far left (blue) under-sample saturation; if too far right, onset (red). Optimum: central LET @ $LET_0 + w$ and left and right points sample <5% and >95% of σ_s .

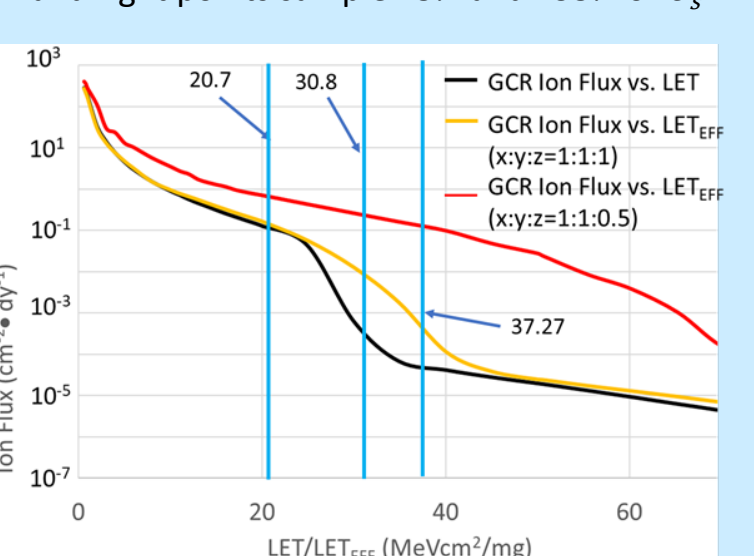


Fig. 2 GCR ion flux falls much more rapidly with LET than with effective LET (LETEFF) for most device sensitive volumes (SV).

Monte Carlo (MC) tools like that introduced at NSREC 2022[7] are well suited to analyzing complex, interacting errors like those of ill-constrained SEE data. The fitting routine—based on a Generalized Linear Model (GLM)[10]—treats Poisson errors and can explore the effects of systematic errors, (e.g. under-constrained onset LET (LET_0) or saturated cross section (σ_s)), as well as evaluate strategies for maximizing the utility of such data. The likelihood-based fitter allows use of a Bayesian fitter if a Prior can be developed to augment the data for one or more of the fit parameters. It also ensures objective and repeatable fits. We implemented the fitter on the Microsoft Excel™ to ensure availability for on-the-fly testing decisions during beam runs. However, the emphasis of the under-constrained-data MC tool is whether data are sufficient to estimate rates or bound them meaningfully. When likelihoods do not decrease rapidly enough to eliminate unreasonable fits from parameter confidence intervals (CI), these rate determinations fail. Specifically, if LET_0 values near 0 and σ_s values >10x the generating value lie within the desired CL, the data cannot meaningfully constrain the fit.

Monte Carlo with Simplified GLM Fitter

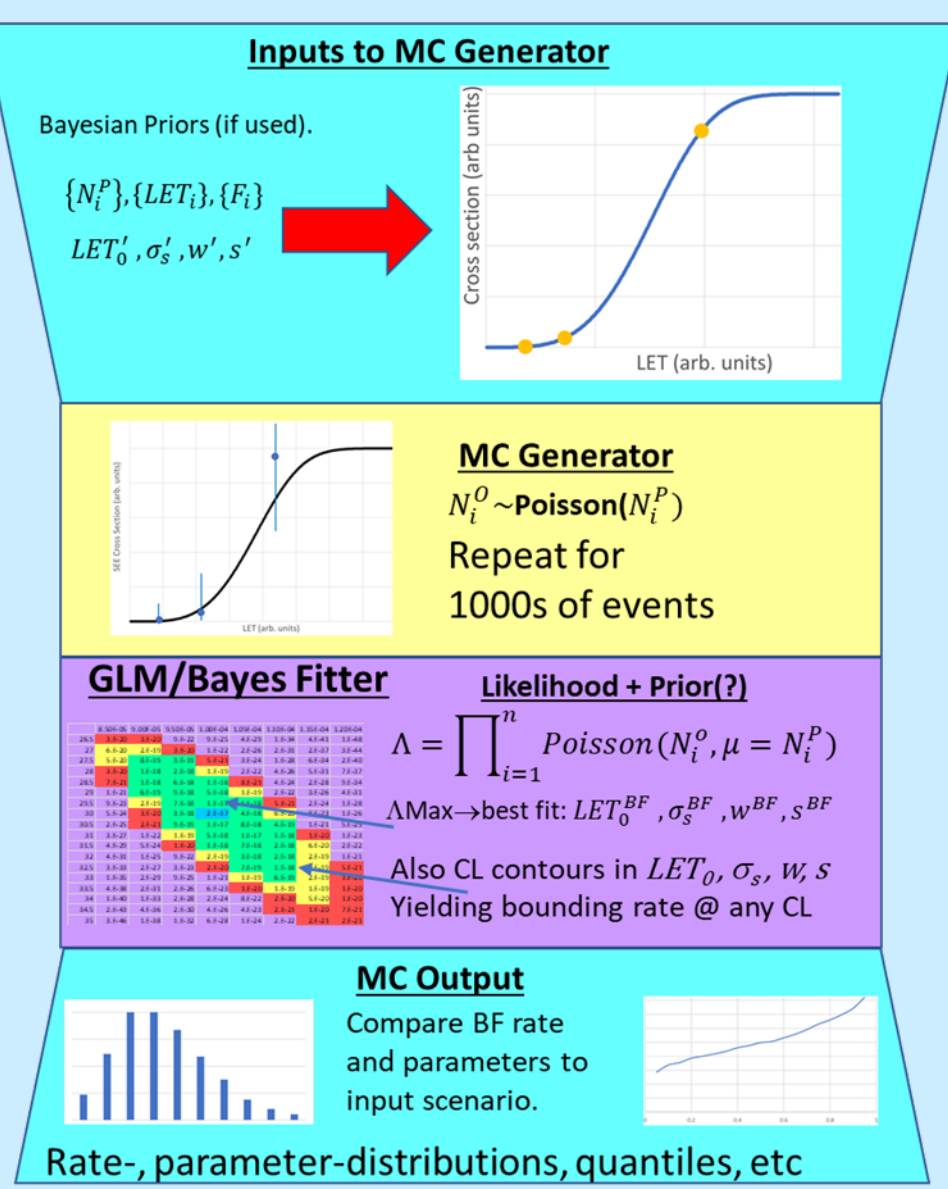


Fig. 3 Schematic of the progression of the MC tool from input through generation, fitting and output. Approach is similar to last year's but with a more limited LET count, more fit-parameter bins for and ability to introduce Bayesian Prior.

- This work builds on last year's MC tool
- Emphasis is on under-constrained data, so allows ≤ 8 LETs
- 10 bins in σ_s and Weibull width w
- 9 bins in LET_0 and Weibull shape s
- Allows Bayesian Prior for LET_0 or σ_s (if none defaults to likelihood)
- Input: Generating Weibull parameters, LETs $\{LET_i\}$, fluence at each LET $\{F_i\}$
 - Mean $H_{EE} @ LET_i = N_i^i = F_i \times \sigma_i(LET_i)$
- MC generates observed SEE N_i^O for each LET ($\sim$ Poisson about N_i^i) (repeat 1000x)
- Fitter constructs Poisson Likelihood Λ and finds fit/rate that maximizes Λ (R_{BF})
- Also finds fit inside parameters' 90% CI that maximizes SEE rate ($R_{90\%WC}$)
- MC Tool output includes:
 - Histograms of fit parameters
 - Quantile plots of R_{BF} and $R_{90\%WC}$
 - % of MC runs where fitter fails to bound σ vs. LET and rate for given CL

Optimizing Ill-Constrained Data

As shown in Fig. 1, optimizing poorly constrained SEE data requires careful placement of the LETs. Repeated trial and error simulations as well as the nature of the cumulative Weibull form indicate that best results are obtained when the central LET (of 3) is placed near $LET_0 + w$, where the argument of the Weibull is 1 and the cross section is $\sim 63.2\%$ of σ_s (regardless of s), and the upper and lower LETs sample <5% and >95% of σ_s . Unfortunately, an arbitrary selection of 3 LETs is unlikely to be optimum for an arbitrary SEE mode in an arbitrary part—nor will one know how close one is to such an optimum.

TABLE I: OPTIMIZED 3-POINT σ VS LET			
$LET_0=15$ MeVcm ² /mg, $\sigma_s=5 \times 10^{-4}$ cm ² , $n=15$			
$s=2$	$s=3$	$s=3.7$	
MeVcm ² /mg	MeVcm ² /mg	MeVcm ² /mg	σ (cm ²)
LET=18	0.00002	LET=20.8	0.000015
LET=30.7	0.00033	LET=30.7	0.00035
LET=37.6	0.00045	LET=37.6	0.00049

We selected test LETs based on criteria such as the proton recoil,[11] GCR LET spectra (see fig. 2), common ions at test facilities,[12] choosing LETs of 37.6, 30.7 and 18-20 MeVcm²/mg. We choose Weibull parameters so the generating σ vs. LET was near optimum.

We look at two Weibulls having the same values for LET_0 , w , and σ_s , but very different shapes ($s=2$ and the more "S" shaped $s=3.7$ —see Table I). For $s=2$, the lowest LET was lowered to 18 MeVcm²/mg so that the lowest cross section would be <5% of σ_s , as failure to lower the LET led to high levels of failure to bound the rate at the desired CL. Fig. 4 illustrates that such optimized datasets do a good job or reproducing the generating rate, especially when large SEE counts ensure low Poisson errors on the few σ points. Convergence is slightly more rapid for $s=3.7$, due to its more rapid saturation.

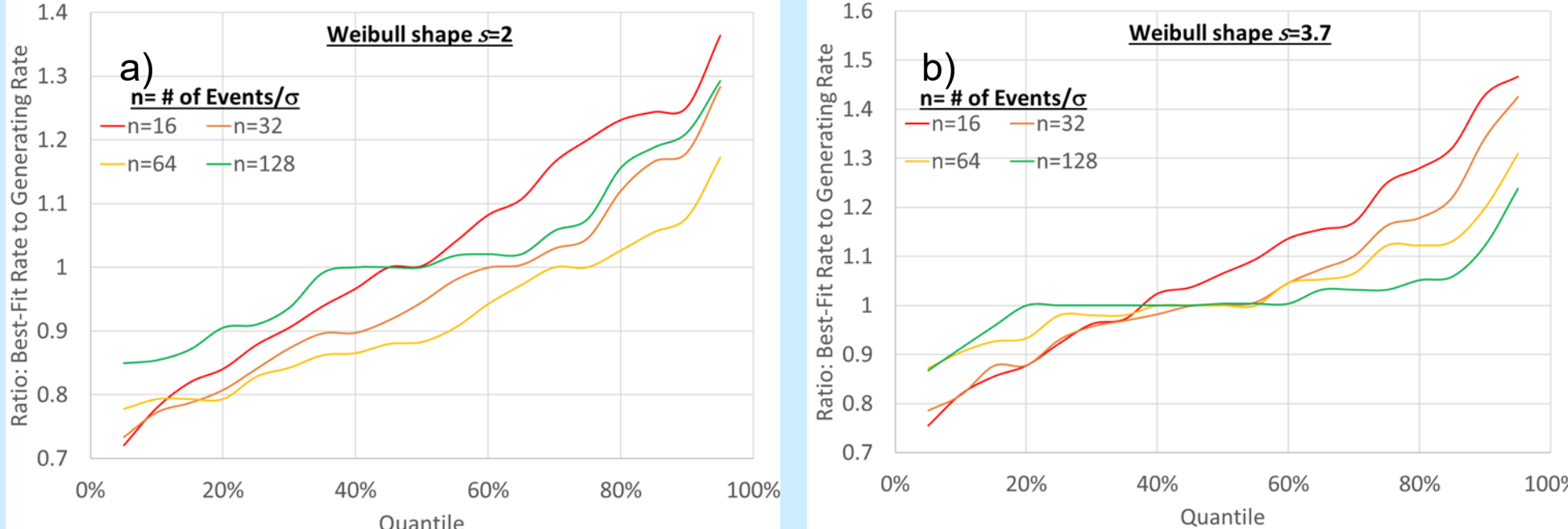


Fig. 4 For optimized, under-constrained data, the fitter finds the generating rate within 1.5x over 90% of the time even for SEE counts as small as 16 per cross section point. The more rapid saturation for $s=3.7$ means results in slightly better convergence than for the slower saturating $s=2$ scenario.

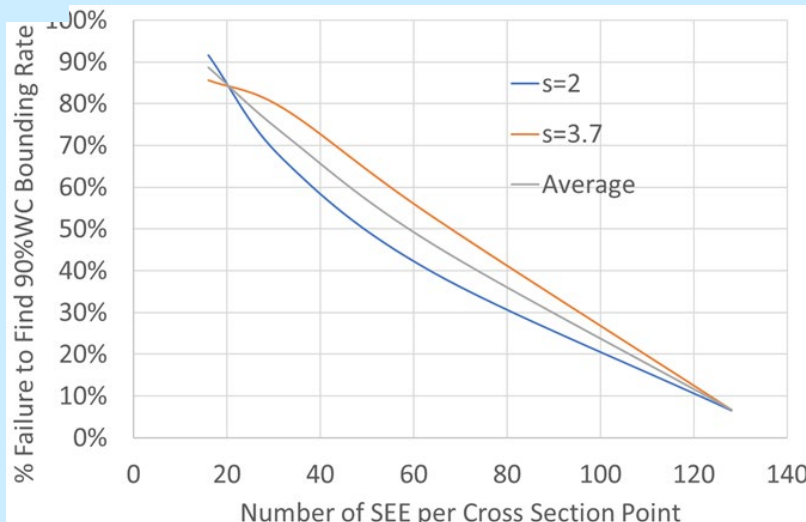


Fig. 5 Proportion of MC events not bounded at a 90% CL falls ~linearly with the SEE count per σ .

Unfortunately, while under-constrained data can estimate SEE rates adequately, bounding the rate for a given CL is more difficult. This is because likelihoods based on a few datapoints decrease slowly, especially for small SEE counts. Fig. 5 shows that the proportion of MC events for which the fitter fails ($\sigma_s > 10x$ or $LET_0 < 0.1x$ their generating values) to bound the SEE rate for the given CL decreases nearly linearly with SEE count.

Estimating The Skew of the LET Triplet

As noted above, under-constrained data are unlikely to be e.g. optimized, and one is also unlikely to know how it diverges from optimum. However, it may be possible to ascertain whether the dataset is skewed leftward or rightward of optimum by comparing the increase in cross section from the lowest to central LET ($\Delta\sigma_L$ on left segment) to the increase in σ from the central to the rightmost LET ($\Delta\sigma_R$ on right segment). (See Fig. 6.) For an optimized dataset, >63% of the rise in σ occurs to the left of the central $LET_0 + w$; so we expect $\Delta\sigma_L > \Delta\sigma_R$ unless, the LET triplet is significantly skewed left of optimum. Fig. 7 summarizes the behavior of the ratio $R_\sigma = \Delta\sigma_L / \Delta\sigma_R$ as a function of Weibull shape s and leftward and rightward skew from optimum. For this study, the left and right LET increments were set equal, but the analysis can be repeated for any LET triplet.

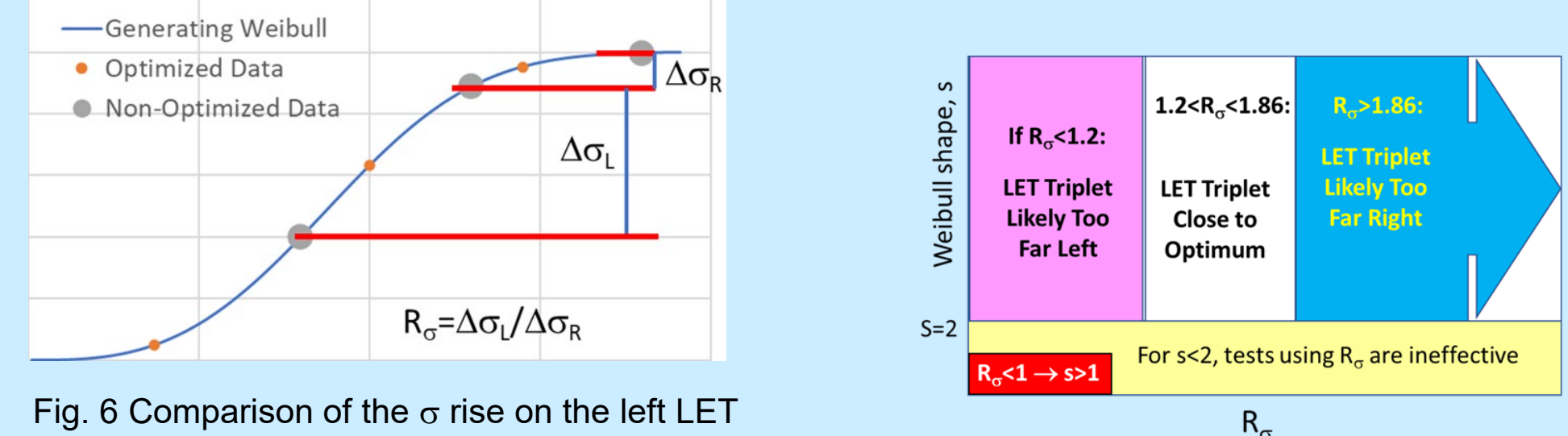


Fig. 6 Comparison of the σ rise on the left LET segment to that on the right segment can reveal whether the LET triplet is skewed right or left.

Fig. 7 A study of equal left and right LET segments reveals the values of R_σ that indicate whether the LET triplet is close to optimal or skewed left or right.

Adding a Bayesian Analysis for SEL

Although the previous sections show that under-constrained σ vs. LET data will not usually be sufficient to estimate or bound SEE rates, such data may be augmented with added information, e.g. in terms of a Bayesian Prior probability distribution ("Prior"). Such a Prior can be developed using a large dataset of SEL susceptibility for a range of commercial Complementary Metal-Oxide-Semiconductor (CMOS) parts (82 parts, 35 functionalities and 20 vendors), compiled by researchers at Conseil Européen pour la Recherche Nucléaire (CERN).[13] Fig. 8 shows the dataset, along with a power-law trendline suggesting LET_0 and σ_s are inversely correlated. Orange circles in Fig. 8 indicate parts for which full Weibull fit to σ vs. LET, and the correlation does appear stronger for these 37 parts ($R^2 > 0.35$).

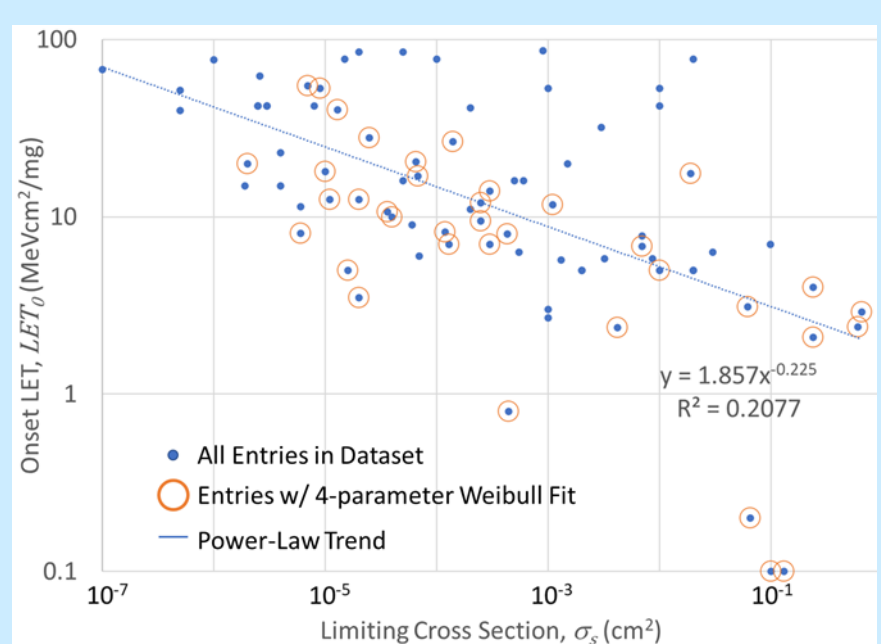


Fig. 8 Large SEL datasets reveal suggest inverse correlations between LET_0 and σ_s despite noise due to variable data quality. (Courtesy of A. Coronetti and R. Garcia-Alia et al. from CERN)

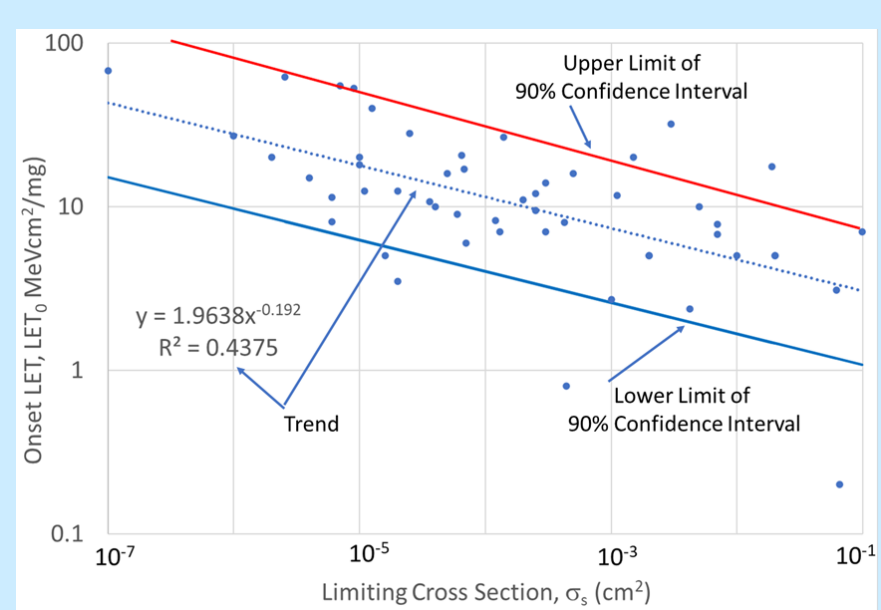


Fig. 9 Including only data with good LET_0 and σ_s estimates reveals the power-law trend (dotted line), suggesting a LN model of the data with constant σ_0 and μ_0 , following the logarithm of the power-law trend. The model's 90% CI (blue and red lines) contains ~90% of the data, so the model adequately bounds the data.

The fact that the Prior can help determine either σ_s or LET_0 emphasizes the importance of skew of the test LETs discussed previously. For data skewed left, (better known LET_0) the Prior constraining σ_s given LET_0 can be used, while for right-skewed data, LET_0 can be constrained given the (likely) better-known σ_s . However, usually, σ_s is easier to determine, since a single high-fluence, high-LET test run is usually sufficient, while determining LET_0 usually requires both a null result and a positive observation of the SEE mode at slightly higher LET. Below, we assess the impact of the Prior determining the distribution of LET_0 in terms of σ_s . We consider 3 different scenarios, each with generating values $\sigma_s = 0.0005$ cm², $w=15$ and $s=2$, but with LET_0 and the LET triplet varying to illustrate how the Prior affects determination of the best fit and 90% WC rates. The scenarios include:

- 1) Minor skew right: $LET_0=9$ MeVcm²/mg; test ion LETs at 18, 30.7 and 37.6 MeVcm²/mg
- 2) Large skew right: $LET_0=9$ MeVcm²/mg, w/ test ion LETs at 25, 35 and 45 MeVcm²/mg
- 3) LET at lower 90% CL: $LET_0=3.5$ MeVcm²/mg ; test LETs at 18, 30.7 and 37.6 MeVcm²/mg

As can be seen in Fig. 11, the Prior has little effect on the best-fit rates. The effect is more significant on the 90% WC rate (Fig. 12). The Bayesian routine results in a probability distribution rather than a likelihood, so determining the 90% confidence contour is a matter of determining the most compact contour that contains 90% of the probability and selecting the WC rate inside that contour. The prior lowers the probability of fits far from the best fit, resulting in a more realistic bound on the rate for the desired CL.

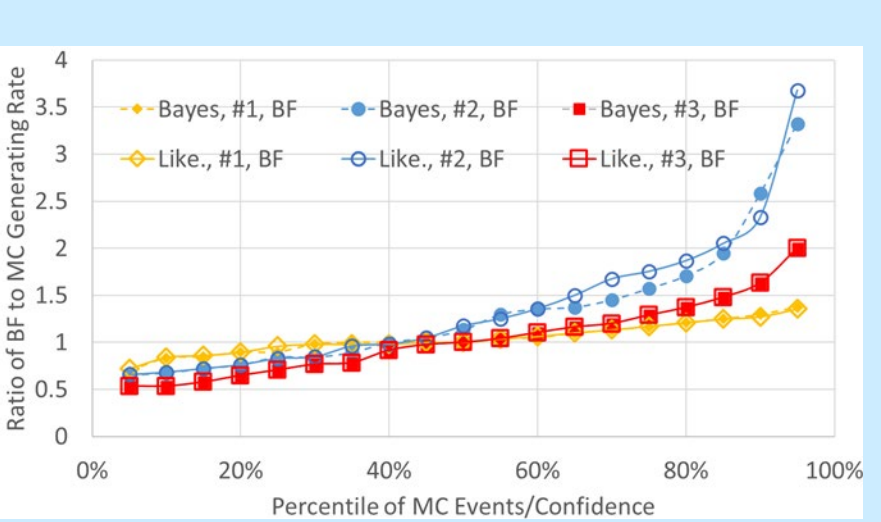


Fig. 11 The LET_0 Prior has little effect on the best-fit rates, even when the LET triplet has a large skew right.

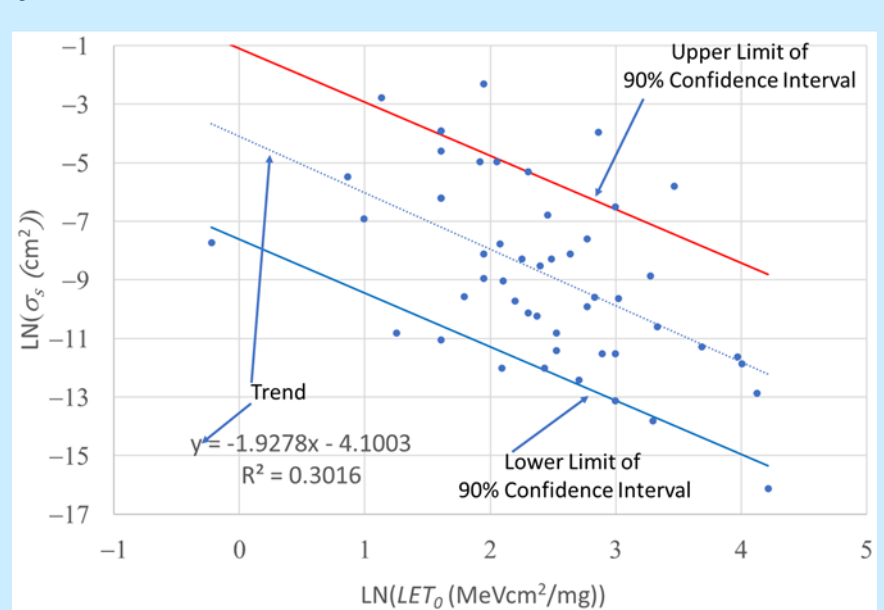


Fig. 10 Because a power-law can be easily inverted, one can use a similar LN model to bound σ_s if LET_0 is known or bounded from below.

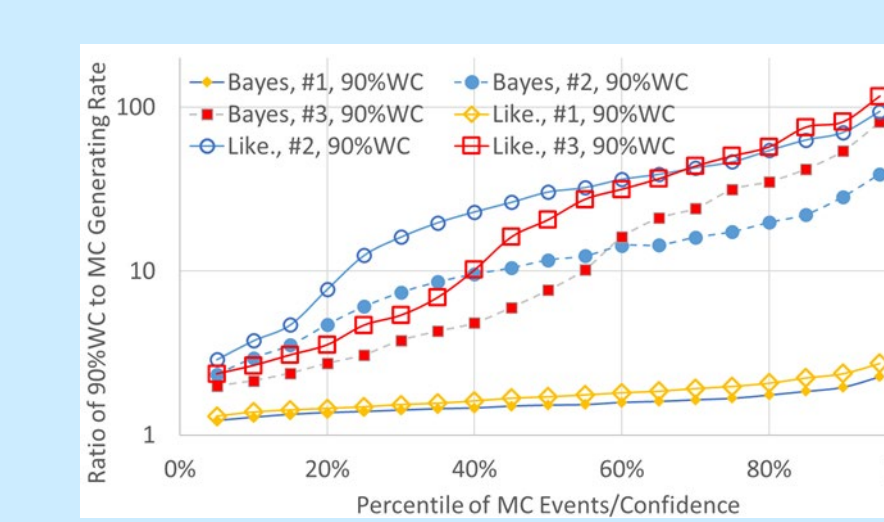


Fig. 12 The LET_0 Prior reduces excess conservatism for the 90% WC rate while still ensuring the 90% WC rate bounds the generating rate >90% of the time.

Using Priors in System-Level Analyses

Perhaps the ultimate under-constrained SEE problem is assessment of the risk posed by SEL for a system in the absence of test data. Although such analysis is difficult and uncertain, it can be useful for allocating scarce design, testing, analysis and mitigation resources. The CERN dataset and resulting Priors can be used to assess the risk SEL susceptible parts pose to a system even before data are gathered.

Consider a system that uses n potentially SEL susceptible parts. We use MC studies to assess how system risk scales with n and as the system is subjected to heavy-ion tests with increasing LET. The MC makes the following assumptions about the probabilities involved:

- 1) 50% of unhardened CMOS parts SEL susceptible; 50% of those fail destructively [15]
- 2) The LET_0 distribution is too broad for parametric fitting; instead, select from among 51 LET_0 s in representative dataset used for Priors for each of 50% parts susceptible
- 3) Use Prior for selected LET_0 to choose σ_s for randomly selected confidence 5% to 95%
- 4) Start with FOM to bound rate: $R_{FOM} = C_E \times \sigma_s / (LET_0 + w(0.288)^{1/s})^2$
 - a) Letting $w \rightarrow 0$, $R_{FOM} \leq C_E \times \sigma_s / (LET_0)^2$ will bound rate (and so risk)
 - b) Take subset of 31 parts with full Weibull fits as representative, note w and s are correlated; randomly select w - s pairs and plug into R_{FOM} for representative rates
- 5) Impose testing up to maximum test LET LET_T that detects all parts with $LET_0 \leq LET_T$
- 6) Repeat 10000 MC events and select 1000th highest system rate=90% WC system

Figs. 13 and 14 show the 90% WC system SEL rate (using methods 4a) and 4b) as a function of maximum test LET for different system complexities ($n=10, 20$ and 40 potentially susceptible parts). Method 4b) makes a difference of ~4x at low test LET and 2x at higher test LET. However, both figures show qualitatively the same behavior—roughly exponential decrease in system rate up to ~35 MeVcm²/mg, with slower decrease above that level, especially for more complex systems ($n > 20$).

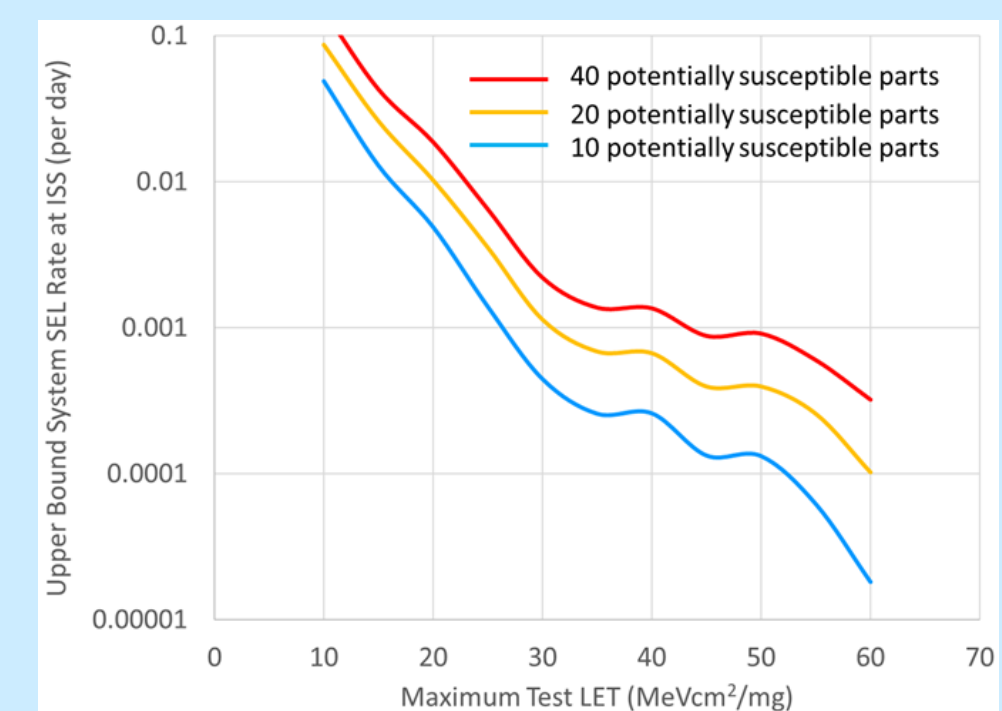


Fig. 13 The 90% WC system-level SEL rate (method in 4a) decreases exponentially up to a maximum test LET of ~35 MeVcm²/mg, but more slowly for higher LETs.

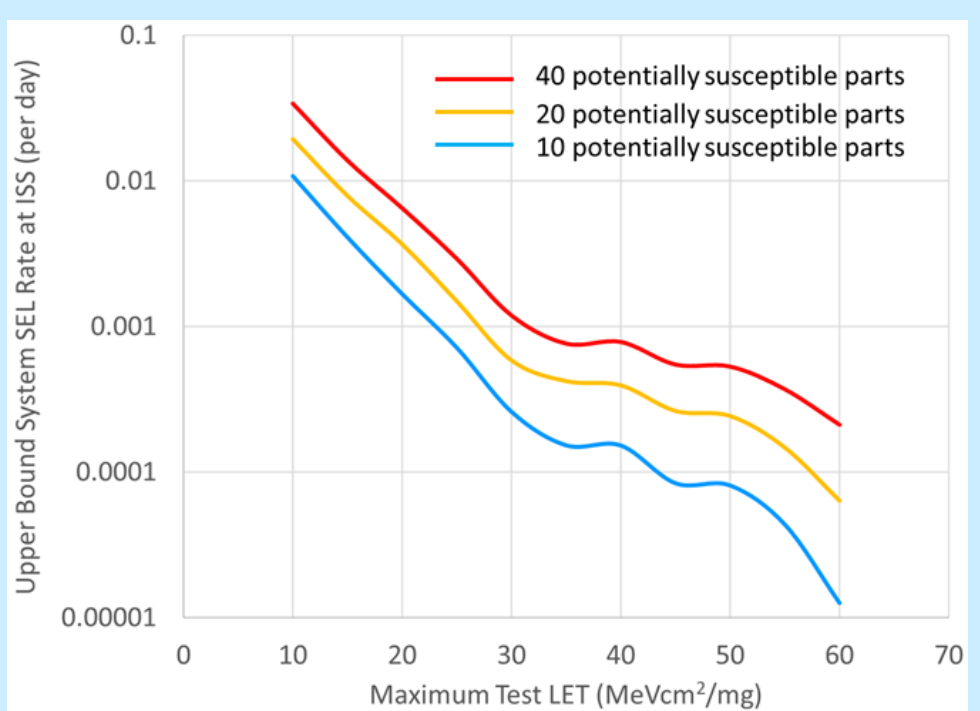


Fig. 14 The 90% WC system SEL rate produced with representative values for s and w exhibits similar behavior, but values are lower by 2-4x.

Discussion and Takeaways

- Under-constrained SEE data are becoming increasingly common
 - Scarce beam-time, complicated SEE behavior of parts, complex test setups all contribute
 - Increasing SEE testing by New Space ventures not having rate estimation as primary goal
- Analyzing such data requires objective, repeatable σ vs LET fitting
 - Monte Carlo tool used here fulfills both criteria + consistent with SEE error contributors
 - Allows exploration of effects of Poisson errors, changing test LETs to sample different portions of σ vs LET and examine σ vs LET characteristics posing greatest difficulties for under-constrained data (e.g. slowly saturating σ vs LET)
- Current study suggests best practices for under-constrained data:
 - There is an optimum condition for an LET triplet—central LET at $LET_0 + w$, with upper and lower LETs sampling >95% and <5% of saturation
 - With only 3 LETs, cannot tell how close to optimal LET selection is for defining σ vs LET
 - If Poisson errors on cross sections negligible, ratio of increase in cross section ($\Delta\sigma_L$) on left LET segment to that on right segment ($\Delta\sigma_R$) can give indications whether LET triplet is near optimal or skewed right or left, especially if σ vs LET is not too slow in saturating ($s < 2$).
 - Even if LET triplet is not optimal, best-fit rate is usually near generating rate; bounding rate diverges because likelihood decreases too slowly to eliminate unreasonable, high-rate fits
- Sometimes convergence can be improved with a Bayesian Prior
 - Example developed using correlations between LET_0 and σ_s in CERN dataset
 - Provides fairly weak constraint on either LET_0 or σ_s , whichever is less well determined
 - Has little effect on best fit, but significantly improves convergence for worst-case rates inside a given confidence contour by eliminating unreasonable, high-rate fits
- Bayesian Priors can also be used to bound *a priori* risk (before testing)
 - Use Monte Carlo to model SEL risk for a system with n potentially susceptible devices
 - Model probabilities and use dataset + Bayesian prior to determine LET_0 and bounding σ_s
 - Use LET_0 and σ_s to bound rates (assuming $w=0$ or representative w - s pairs)
 - Use 90% WC system rate for MC events as statistic and measure how various strategies affect it (e.g. testing potentially susceptible parts to some minimum test LET).

Conclusions

The increasing prevalence of under-constrained SEE data—for whatever reason—has increased the need for tools to assess the limitations of such data and to increase its utility. The tools introduced in this work represent a starting point. The MC tool allows the effects of complex, interacting statistical and systematic errors on fits to under-constrained SEE data to be investigated in a repeatable and objective manner. Doing this, one finds that there is an optimal placement of an LET triplet for retrieving a generated Weibull fit—with the central LET at $LET_0 + w$, and the upper and lower LETs sampling σ vs. LET above 95% and below 5% of saturation. Unfortunately, with only 3 LETs, one cannot tell how close to optimum the experiment is. However, by looking at the behavior of the fitting form (e.g. ratio of cross section increases on the left and right segments of the triplet (R_σ)), one can often determine whether the triplet is close to optimal or skewed left or right, as long as Poisson errors on cross sections are negligible and σ vs. LET does not saturate too slowly ($s \geq 2$). Knowing which way the LET triplet is skewed can in turn indicate whether LET_0 or σ_s is more poorly determined and suggest characteristics of a Prior distribution to supplement the data and improve results.

Although under-constrained data poses significant challenges for the radiation analyst, careful analysis can maximize its utility while limiting risks. This requires understanding the data (e.g. by Monte Carlo studies), the characteristics of the curve form fit to the data (e.g. in terms of R_σ), and if possible, supplementing the data—for example, using Bayesian priors based on analyses of trends in large datasets relevant to the test parts. Better understanding how to maximize utility and minimize risks of under-constrained data will likely pay dividends as the trends underlying its increase persist.

Acknowledgment

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