

Including Survivors in Probabilistic TID Failure Assessment

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Acronyms



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- **TID – total ionizing dose**
- **RHA – radiation hardness assurance**
- **RDM – radiation design margin**
- **COTS – commercial off-the-shelf**
- **CDF – cumulative distribution function**
- **PDF – probability density function**
- **CL – confidence level**
- **MC – Monte Carlo**

- **RHA has evolved to use probabilistic environment dose models ([1] and [2])**
- **Prior military guidelines used worst-case constants for environment dose and part failure dose to calculate RDM and categorize device hardness [3]**
 - Does not account for the variability of the environment or device performance
 - Incorporating all aspects of failure variability allows for more flexibility in determining the suitability of the part for a mission
- **A new method for RHA was developed in [4] and [5] to calculate a failure probability and establish a confidence level for a part – requires failure data**
- **This work expands on [5] to incorporate datasets containing survivors or a mixture of failures and survivors**

Part Number	Manufacturer	Device Function	Sample Size	Test Env.	Test Facility (Test Date)	Test Results (Effect, Dose Level/Energy, Results)
JANS2N2907AUB	Semicoa	Transistor	88	Gamma	GSFC (Jun 2021)	TID, LDR, No parametric failures ≤ 30 krad(Si). [10]
JANS2N5339	Semicoa	Transistor	10	Gamma	GSFC (Sep 2021)	TID, LDR, No functional failures ≤ 36 krad(Si).
SY88422L	Microchip	Laser Driver	2	Gamma	GSFC (Jul 2021)	TID, HDR, 100 krad(Si), No radiation induced degradation of timing performance for 10 ns input pulses during testing was observed. [12]

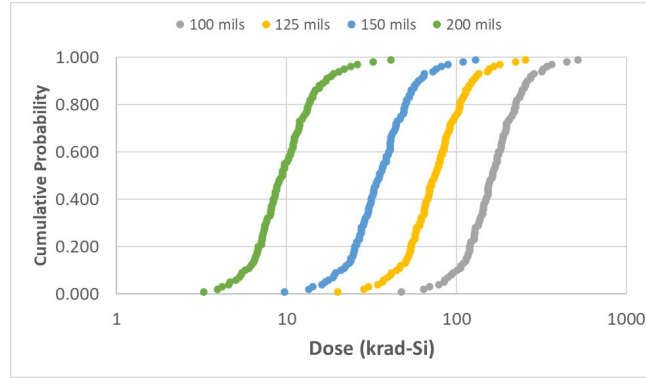
From NASA Goddard Space Flight Center's Recent Radiation Effects Test Results (2022)

Probabilistic Framework

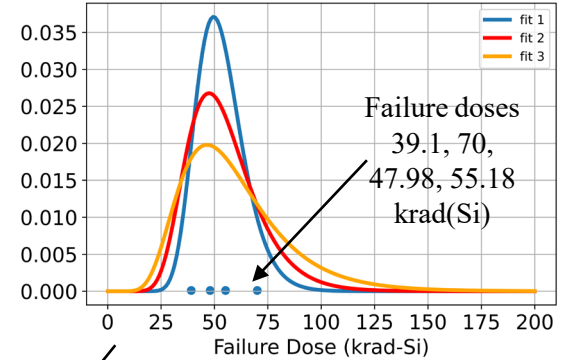


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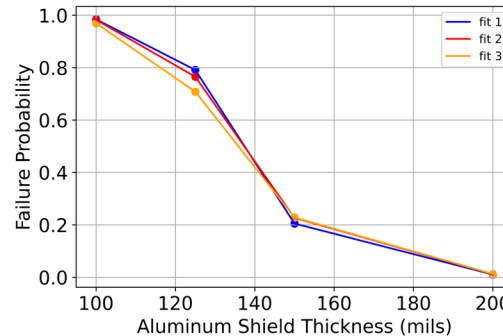
- Integration with environment and device distributions -> encompass all failure variability
- Small sample sizes create uncertainty in device behavior distribution fit – what are the true fit parameters μ_g and σ_g ?



Environment dose CDF (AP9/AE9/ESP, transported through shielding)



$$P_{fail} = \int [1 - H(x)] \cdot g(x) dx$$



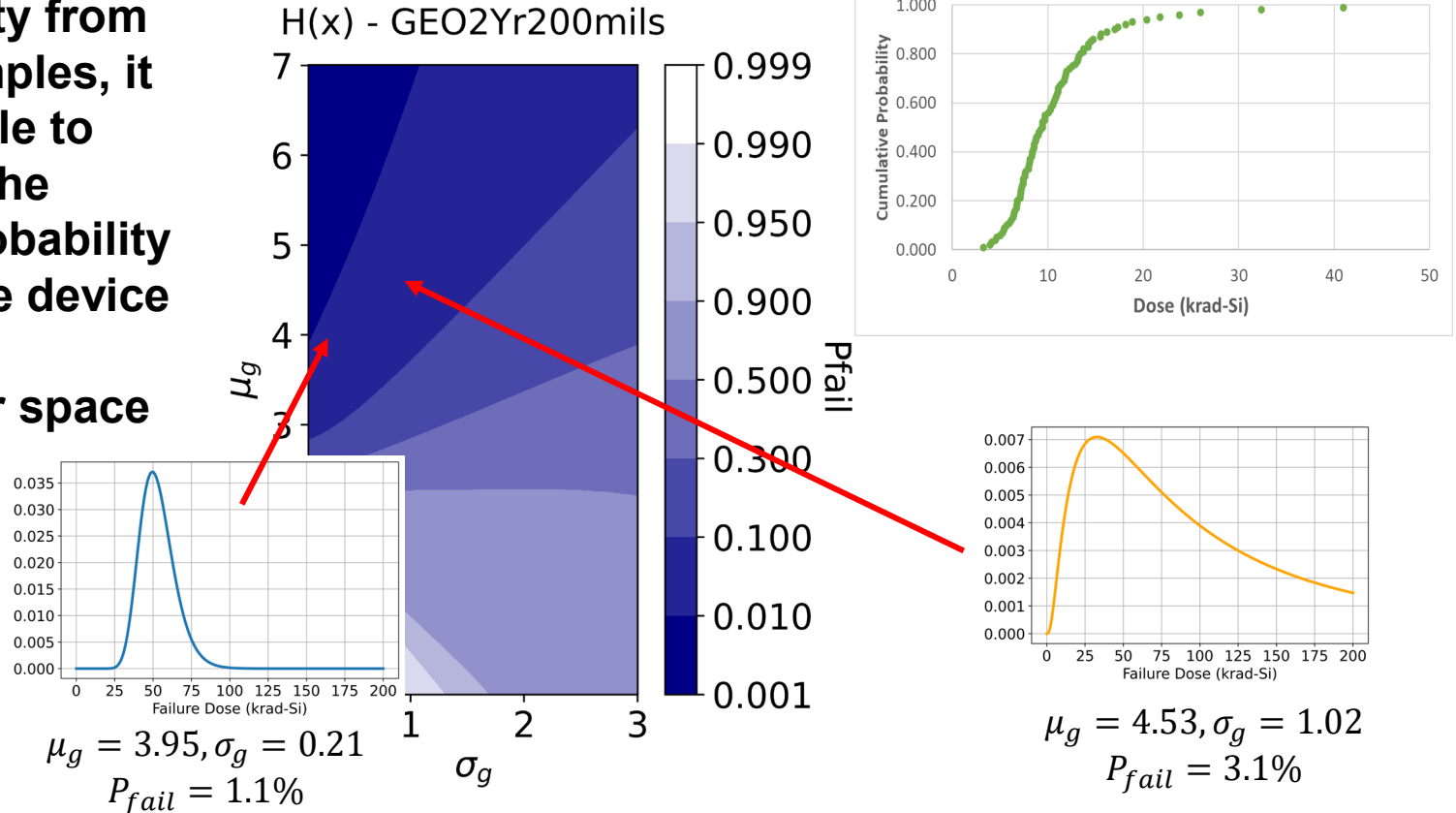
(Xapsos et al., 2017)

On-Orbit Failure Probability over Parameter Space



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- Because of the uncertainty from small samples, it is desirable to examine the failure probability across the device behavior parameter space



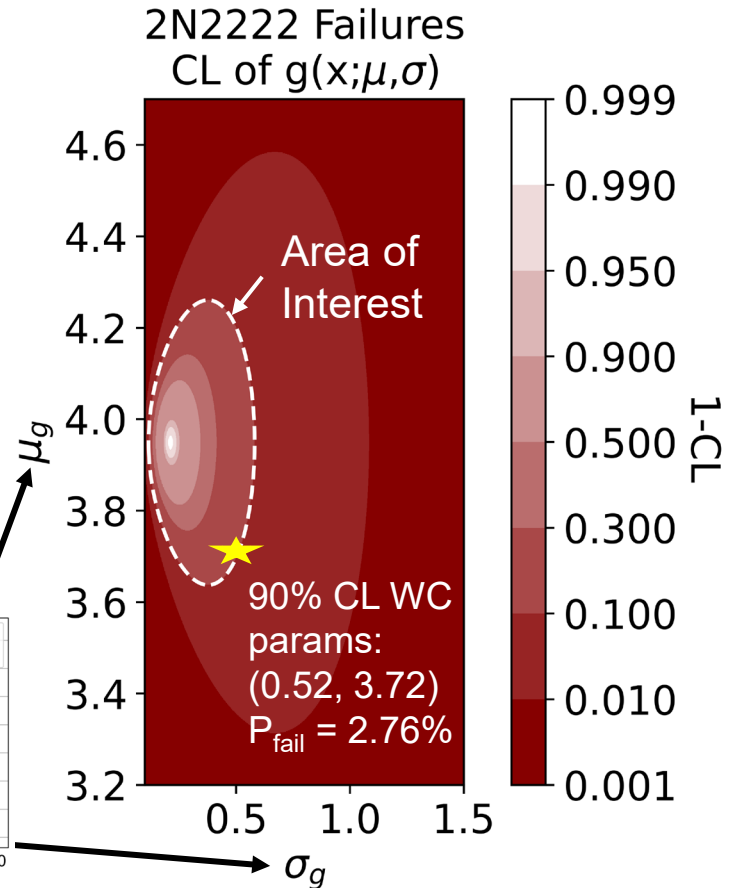
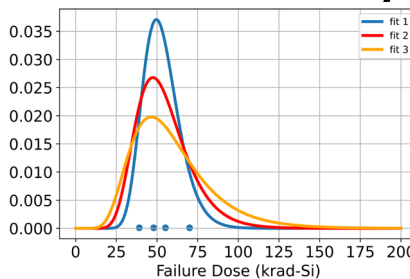
Likelihood-based Confidence



- To constrain parameter space and attach confidence to the failure probabilities, use the likelihood of the device behavior distributions
- Likelihood ratios = confidence gradients [5],[6]
 - Bind parameter space to most likely fits
 - Dashed line = 90% CL contour
 - Max. P_{fail} generated with parameters in area of interest = 90% CL WC P_{fail}

$$Likelihood = L = C \prod f(t_i, \mu, \sigma)$$

(Ladbury et al., 2021)

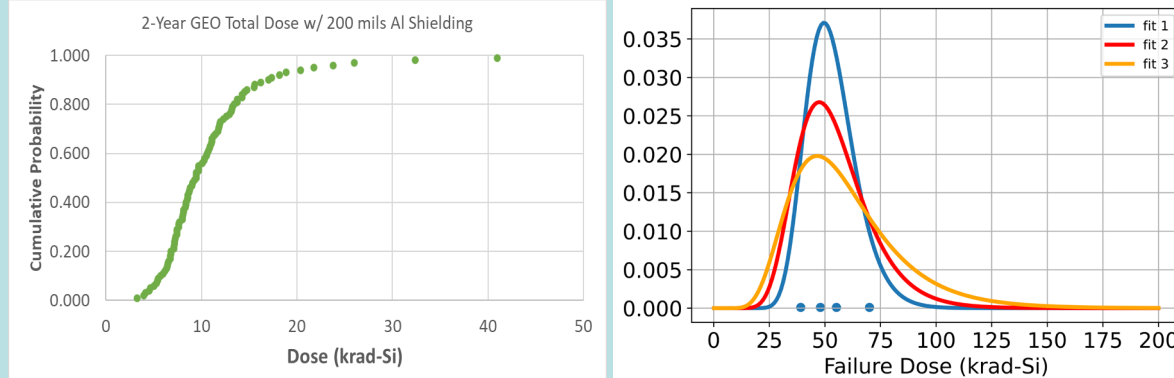


Probabilistic Framework w/ Family of Curves

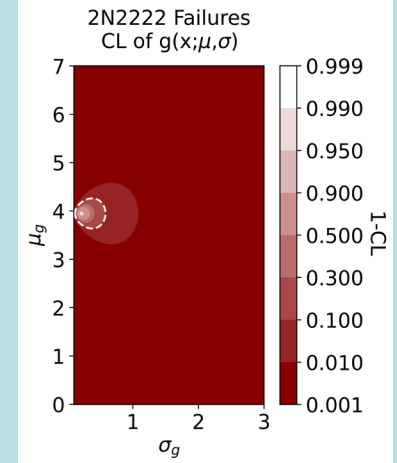


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1. Integrate

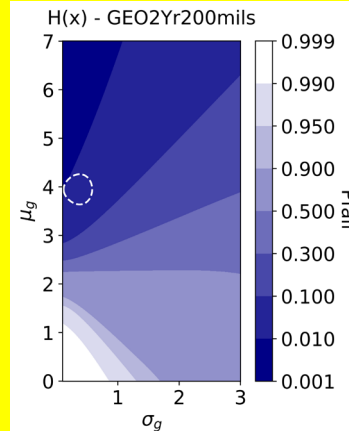


2. Apply contour mask to param space



- **After integrating over the device behavior parameter space, apply 90% confidence contour as a mask to bound the space and determine worst-case P_{fail}**

3. Bounded P_{fail} space



Survivor Data – How to use it?



- Many parts are tested to a certain dose level rather than failure
- If parts survive TID testing, can this information be used to constrain mission failure probability?
- This type of data is known as type-I censored data (datapoints not monitored to failure), and type-I censored likelihood can be used to constrain the parameter space

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From NASA Goddard Space Flight Center's Recent Radiation Effects Test Results (2022)

Type-1 Censored Confidence Contours



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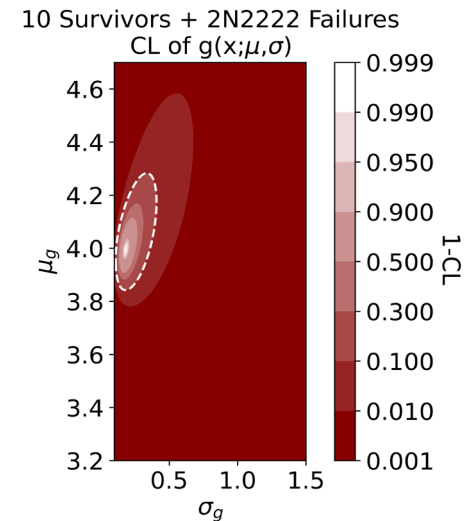
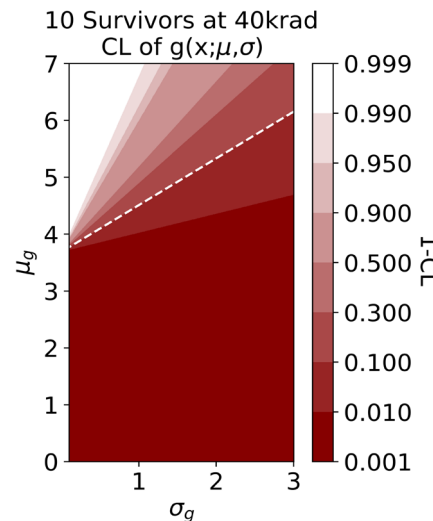
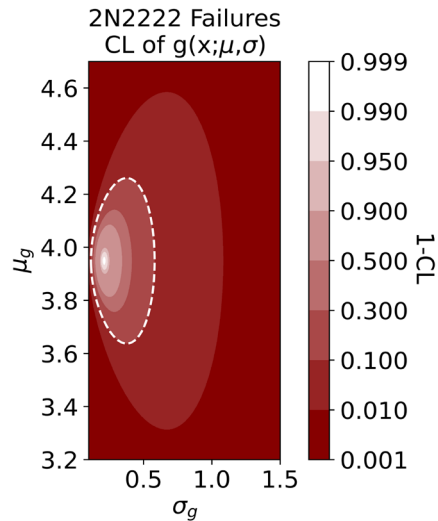
Type-1 Censored Likelihood =

$$L = C \left(\prod_{i=1}^r f(t_i) \right) [1 - F(T)]^{n-r}$$

- T = dose survivors tested to
- n = sample size
- r = # of failures
- t_i = failure dose of i^{th} failure
- f = device behavior PDF
- F = device behavior CDF

Uncensored data w/ 4 failure doses (original)

Type-1 Censored data: dataset where not all parts tested to failure (i.e., composed of some/all survivors) [7]

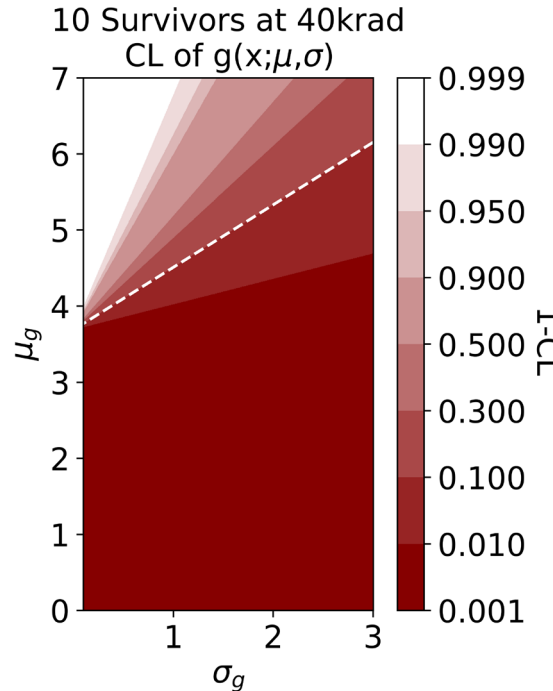


Bounding Failure Probability

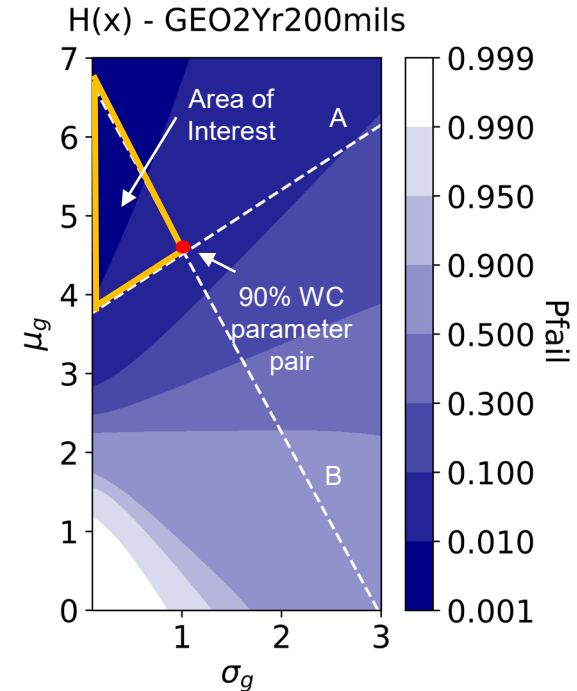


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- As before, the confidence contours can be used to constrain the parameter space and find a worst-case P_{fail} at the desired confidence
- Survivor data is less restrictive than failure data – use upper bound based on engineering judgement



Lower bound (A)
(from data)



Bounded P_{fail} space
(about 3.1% WC)

Examples



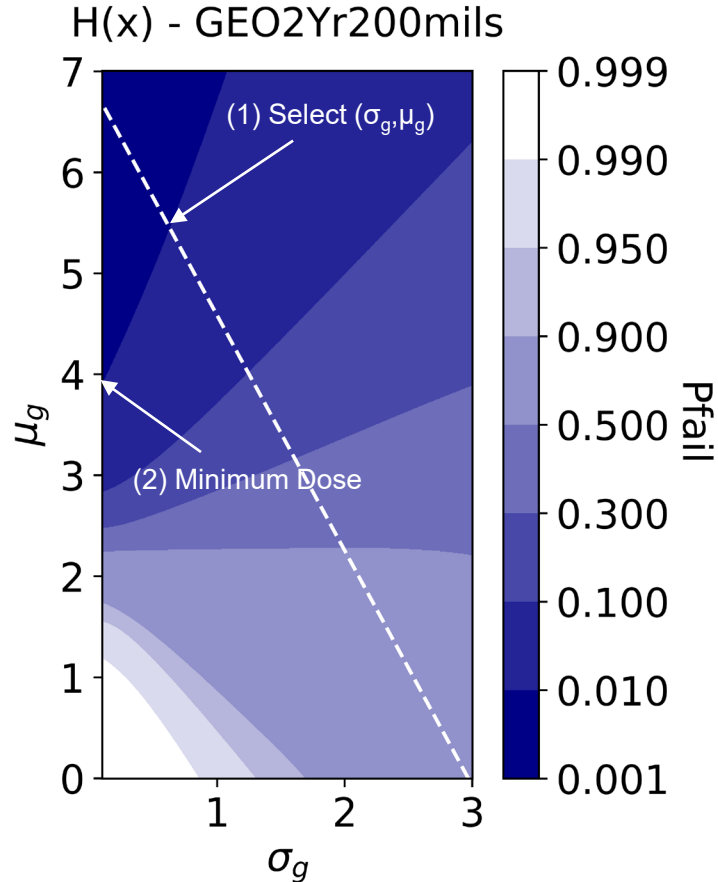
- **Both sample size and amount of overtest will affect the WC P_{fail}**
 - Need to test many parts if dose tested to is lower, and even high tested doses only constrain P_{fail} so much when sample size is small
- **Any failure data will dominate the P_{fail} calculation over any survivor data**

2 Year GEO, 200 mils Al		
Manufacturer Part Number	Test Results	90% Confidence WC Failure
Semicoa JANS2N2907AUB	88 survivors to 30 krad(Si)	1.5
Semicoa JANS2N5339	10 survivors to 36 krad(Si)	3.7
Microchip SY88422L	2 survivors to 100 krad(Si)	10
Microchip MIC4427	1 failure at 20 krad(Si), 7 survivors to 30 krad(Si)	17.9

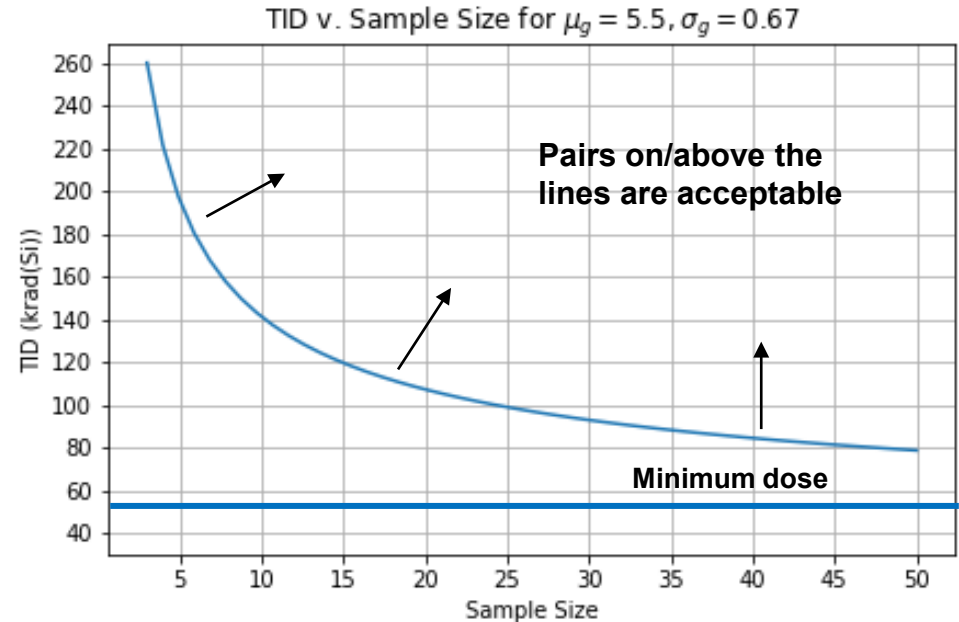
Test Planning – Optimizing Between Sample Size and Beam Time



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- In addition to post-test analysis, the framework can be applied to test planning to determine sample size and overtest needed
 - Optimize sample size and tested dose for budget and timing constraints to meet survival requirements



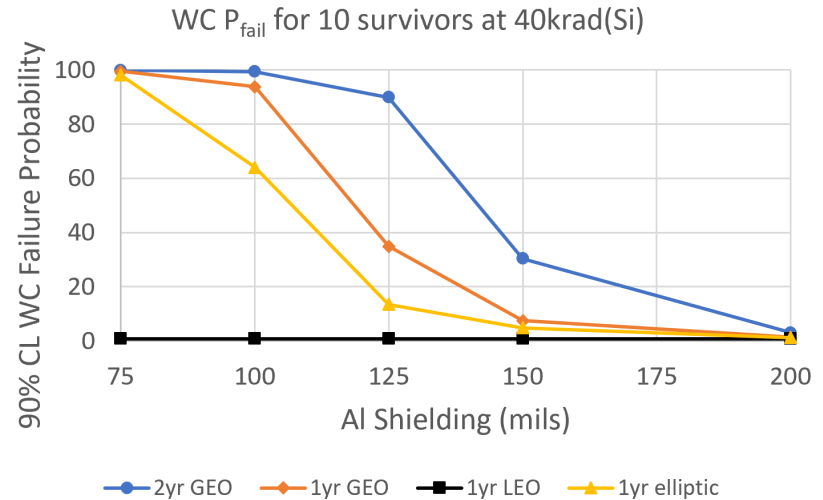
- **Survivors can be used for a complete assessment of a device's failure probability in space environments**
 - Failure data dominates constraints, but survivor data still provides useful bounds on the parameter space
 - Large portions of the failure space can be excluded based solely on survivors, eliminating high failure probability regions
- **Applications: test planning, heritage data**
- **The framework allows an engineer to consider all available survival and failure data on a candidate device**
 - Permits a quantitative assessment of survival in a variable space environment
- **Full work will be presented as a poster at NSREC; analysis will become available on RADHUB in the future**

1. G. Ginet, et al., “The AE9, AP9 and SPM: New models for specifying the trapped energetic particle and space plasma environment,” *Space Sci. Rev.*, vol. 179, nos. 1–4, pp. 579–615, Nov. 2013.
2. M. A. Xapsos, et al., “Probability model for cumulative solar proton event fluences,” *IEEE Trans. Nucl. Sci.*, vol. 47, no. 3, pp. 486–490, Jun. 2000.
3. MIL-HDBK-814: Ionizing Dose and Neutron Hardness Assurance Guidelines for Microcircuits and Semiconductor Devices, Department of Defense, 1994.
4. M. A. Xapsos, et al., “Inclusion of radiation environment variability in total dose hardness assurance methodology,” *IEEE Trans. Nucl. Sci.*, vol. 64, no. 1, pp. 325–331, Feb. 2017.
5. R. Ladbury and T. Carstens, “Development of TID hardness assurance methodologies to capitalize on statistical radiation environment models,” *IEEE Trans. Nucl. Sci.*, vol. 68, no. 8, pp. 1736–1745, Aug. 2021.
6. Y. Pawitan, “2.6 Likelihood-based intervals,” in *In all Likelihood: Statistical Modelling and Inference using Likelihood*, Oxford: OUP Oxford, 2014.
7. “8.4.1.2. Maximum likelihood estimation,” NIST/SEMATECH e-Handbook of Statistical Methods, 12-Apr-2012. [Online]. Available: <https://doi.org/10.18434/M32189>. [Accessed: 09-Dec-2022].

Extra: Other Environments



- Any environment can be used with this framework by ranking or fitting MC trials
 - Sample environments shown follow expected trends with duration and shielding thickness
- The probabilities listed below are worst-case for survivor data
 - A high worst-case failure probability does not mean the part *will* fail – only that there is not enough info from the test to constrain P_{fail} a meaningful amount



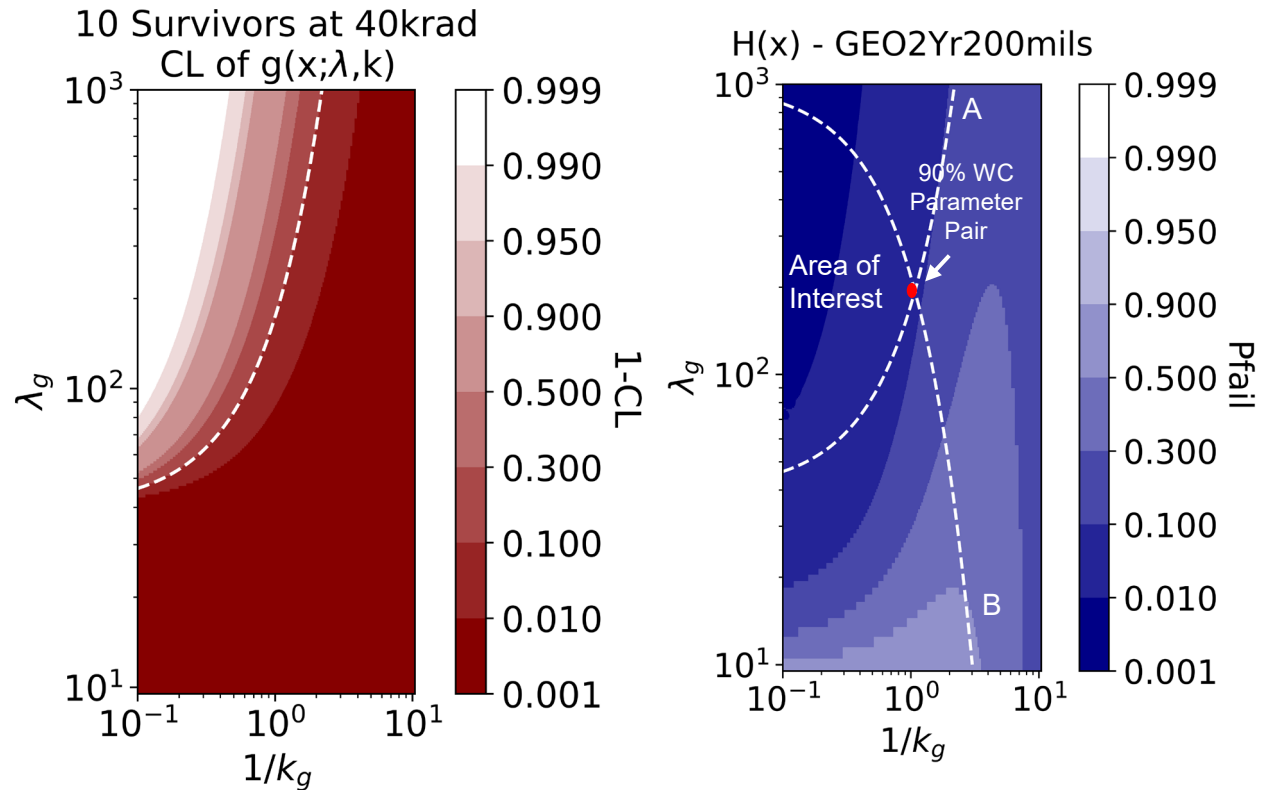
Note: GEO data incorporates IRENE and ESP, LEO and elliptical orbits only use IRENE

Extra: Other Device Failure Fits – Weibull



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- While previous slides used lognormal fits of the device behavior, any fit can be used
 - Weibull fits of 10 survivors shown
- The type of fit selected will affect the worst-case P_{fail} and must be chosen mindfully



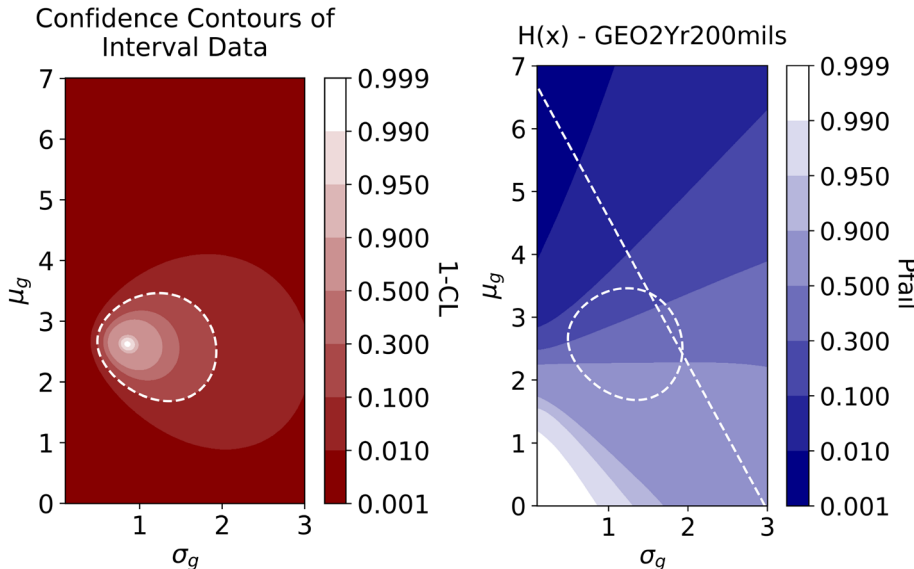
90% WC $P_{fail} \approx 7.3\%$
(lognormal fit produced WC $P_{fail} \approx 3.1\%$)

Extra: Incorporating Step Stress



- **Step-stress: device parameters measured after set intervals of irradiation rather than while being irradiated (cannot determine exact point of failure)**
- **AD9050 TID test results:**

Dose Intervals (kradSi)	# Failures
0-5	1
5-10	2
10-20	0
20-30	3
30-50	1



Readout Data Likelihood =

$$L = C \left(\prod_{i=1}^k [F(T_i) - F(T_{i-1})]^{r_i} \right) [1 - F(T)]^{n - \sum_{i=1}^k r_i}$$

<https://www.itl.nist.gov/div898/handbook/apr/section4/apr412.htm>

Evaluation Of High Performance Converters Under Low Dose Rate Total Ionizing Dose (TID) Testing For NASA Programs (1998)



- **Parts flown on previous missions can also be used to constrain the parameter space, treat as survivors**
- **Caveats**
 - Mission qualification documents list upper bound on dose encountered
 - Heritage parts may be from different lots, need to account for lot-to-lot variability
 - Previous mission doses may be less than current mission

Extra: Key Assumptions



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- **The device failure distribution is well-behaved (not bimodal or thick-tailed)**
 - Examined lognormal and Weibull fits
- **Only one lot is being considered (neglecting lot-to-lot variability)**
- **The upper bound of realistic device performance is 99% of devices failing at 1 Mrad(Si)**