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Mars Science Laboratory: Launch Safety Analysis

David G. Robinson, PhD

Southwestern Indian Polytechnic Institute
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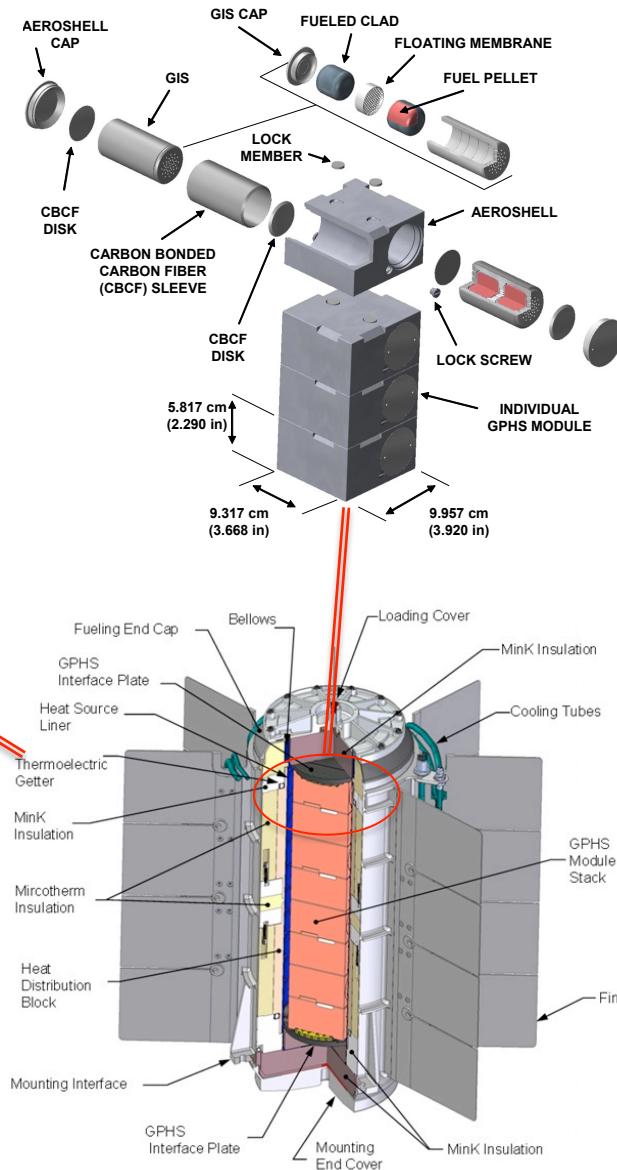
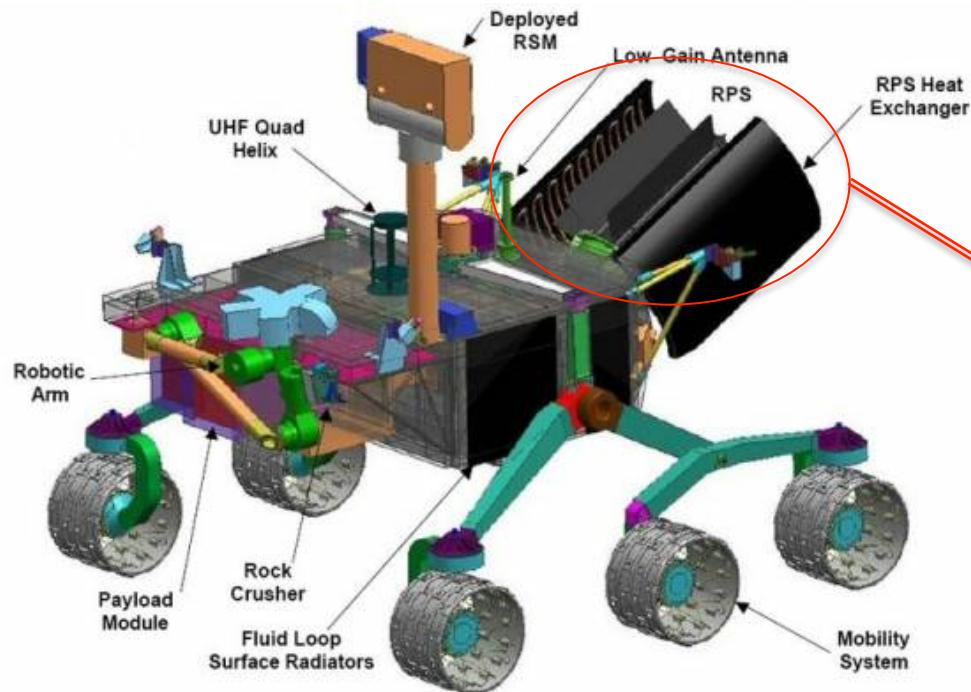


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Introduction

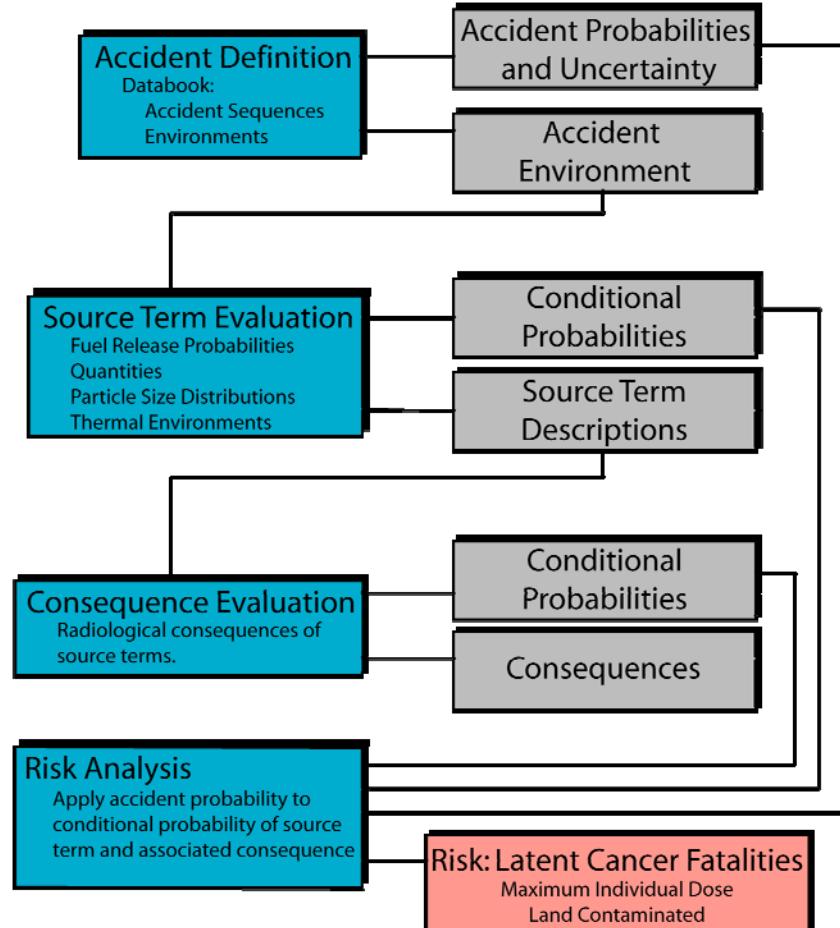
Objective: introduce the risk analysis methodology used to support the launch of the Mars Science Laboratory.

The MSL rover design uses a Radioisotope Thermoelectric Generator (RTG) to provide continuous power on the Martian surface. This particular RTG contains eight General Purpose Heat Source (GPHS)

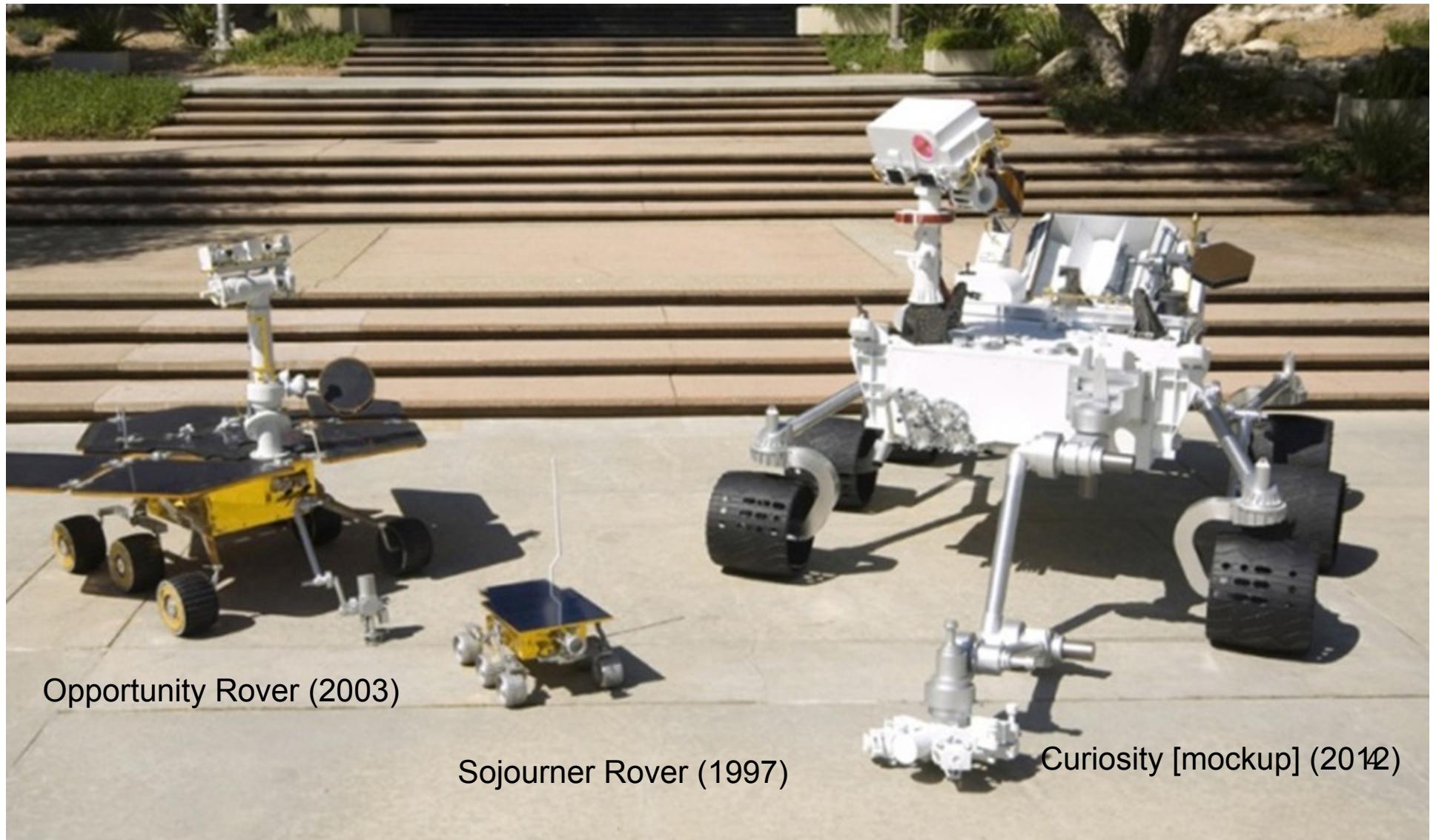


Basic Elements of Risk Analysis

- Risk results reported by:
 - Representative Accident Scenario
 - Mission Phases: pre-launch, low altitude, high altitude, suborbital reentry, orbital reentry
 - Overall Mission
- Released Source Terms
- 50 year Health Effects
- Maximum Individual Dose
- Land Contamination at selected levels

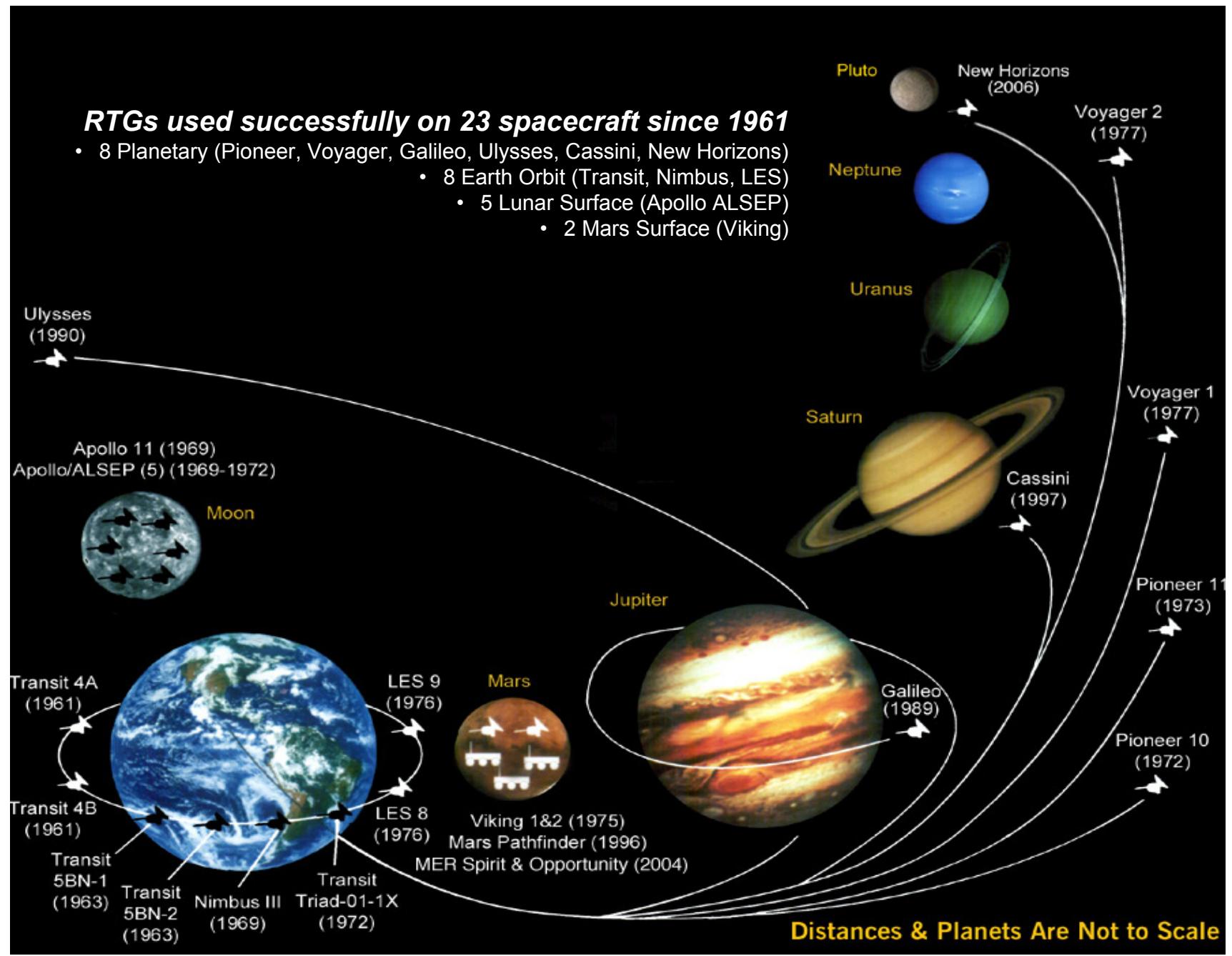


Comparison of Mars Rovers

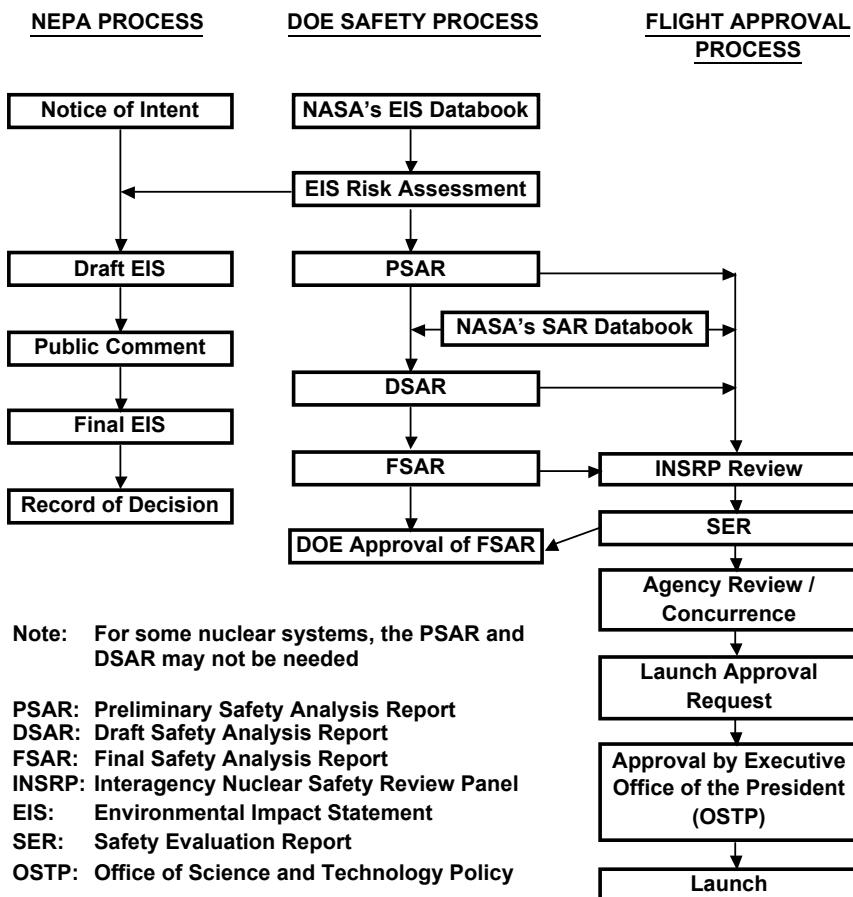


RTGs used successfully on 23 spacecraft since 1961

- 8 Planetary (Pioneer, Voyager, Galileo, Ulysses, Cassini, New Horizons)
 - 8 Earth Orbit (Transit, Nimbus, LES)
 - 5 Lunar Surface (Apollo ALSEP)
 - 2 Mars Surface (Viking)



Launch Approval Process



The Launch Approval Process is implemented through Presidential Directive / National Security Council Memorandum 25 (PD/NSC-25).

This process independently validates the safety of use on a given mission.

Launch System - Atlas V 541

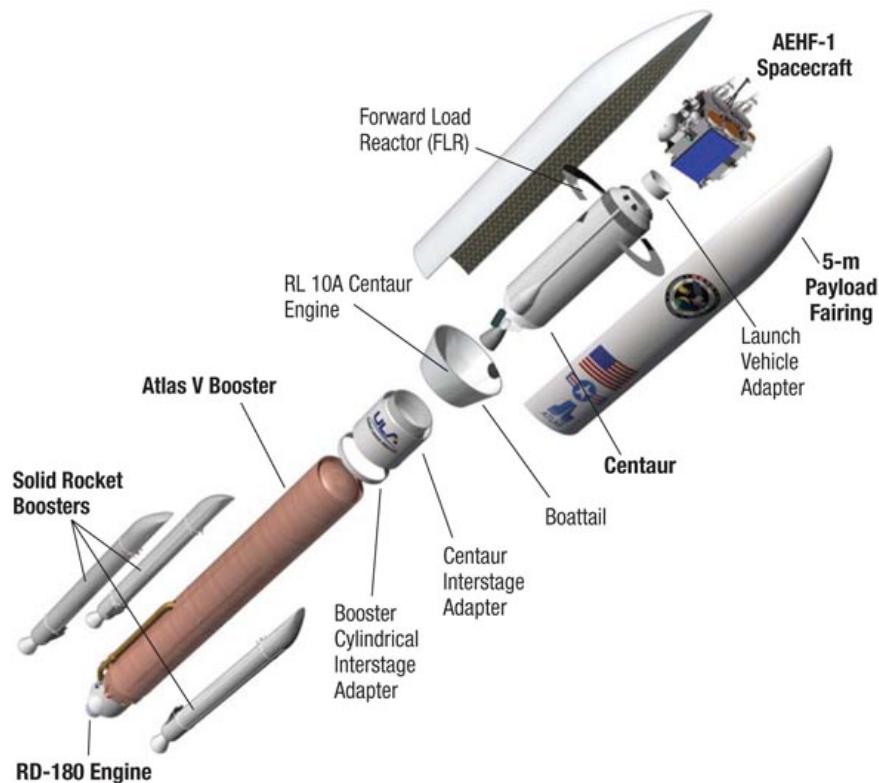
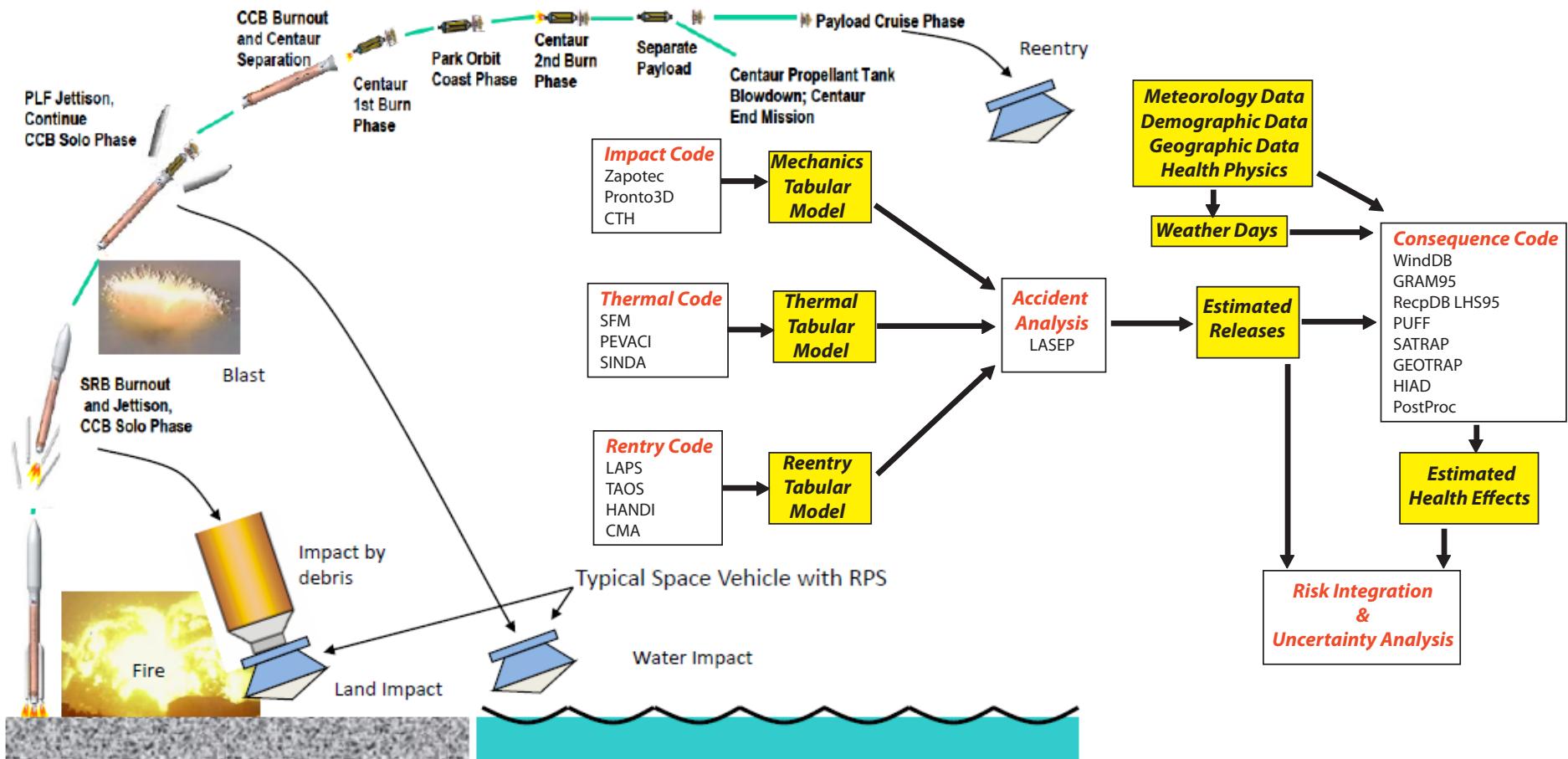


Image: Atlas V 531- United Launch Alliance

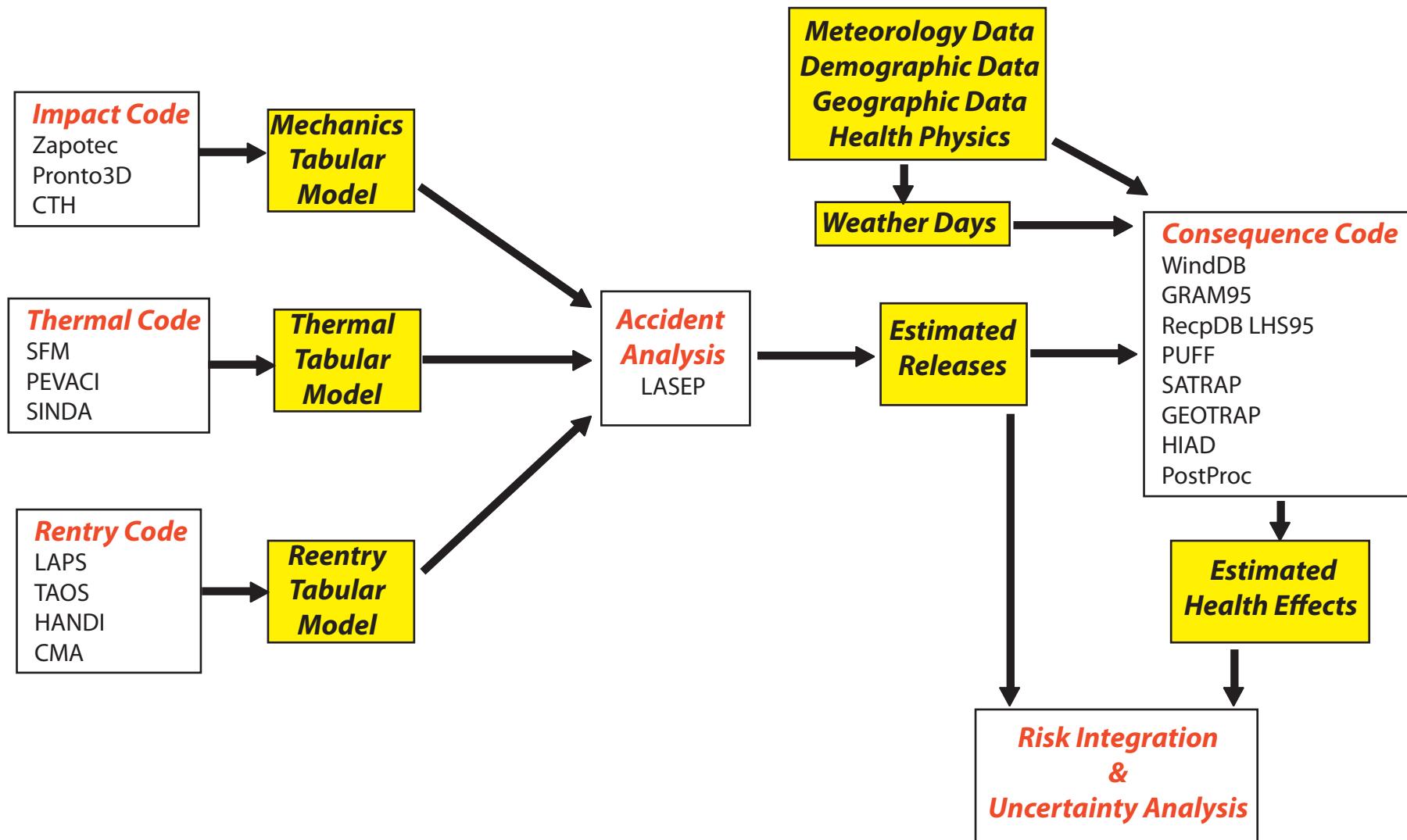


Image: Lockheed-Martin Pluto New Horizons Launch

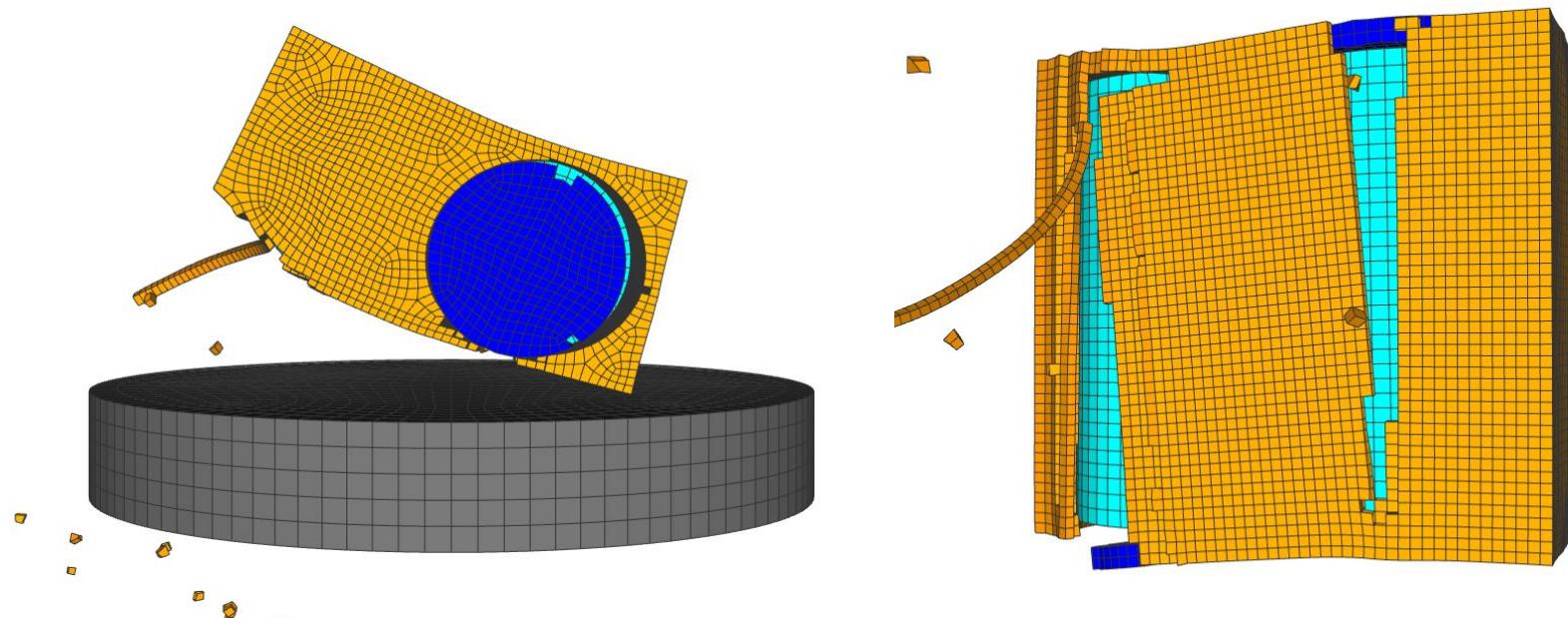
General Risk Analysis Approach



Flow of Uncertainty

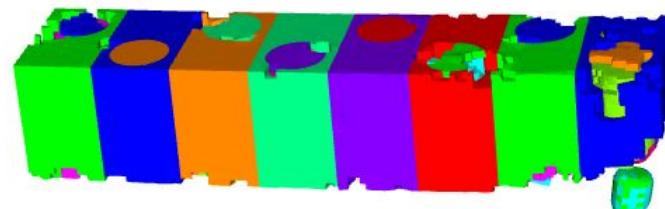
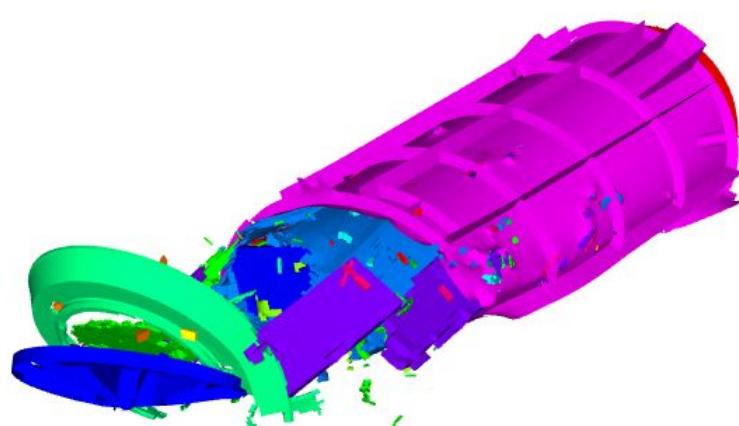
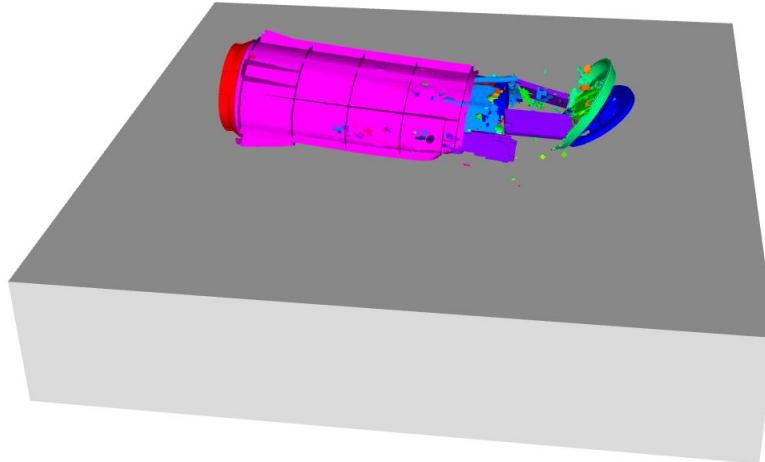


Impact Data vs. Detailed Model

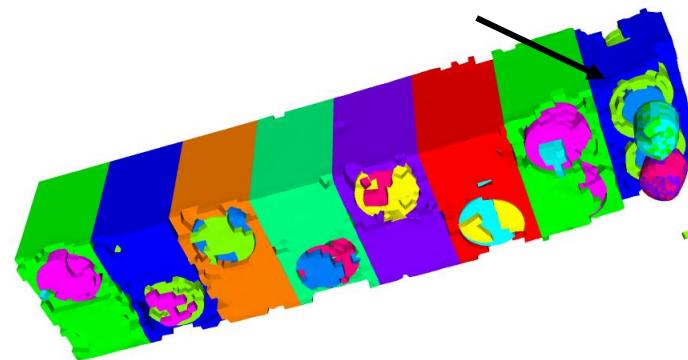


Impact codes are benchmarked using test data

Typical Results for Concrete Impacts



Ejected Fuel Clads

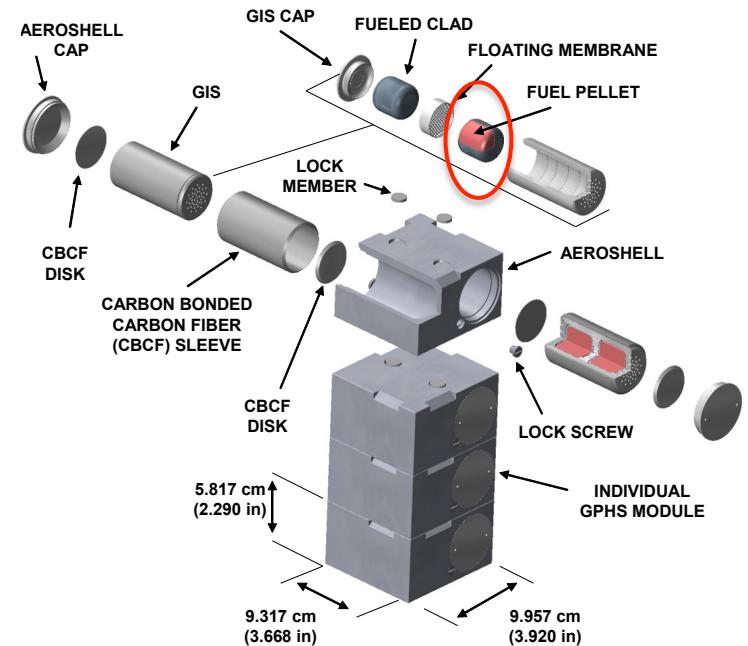


Requires numerous runs on Sandia's Thunderbird supercomputer

Example of Detailed Uncertainty Analysis: Release Model

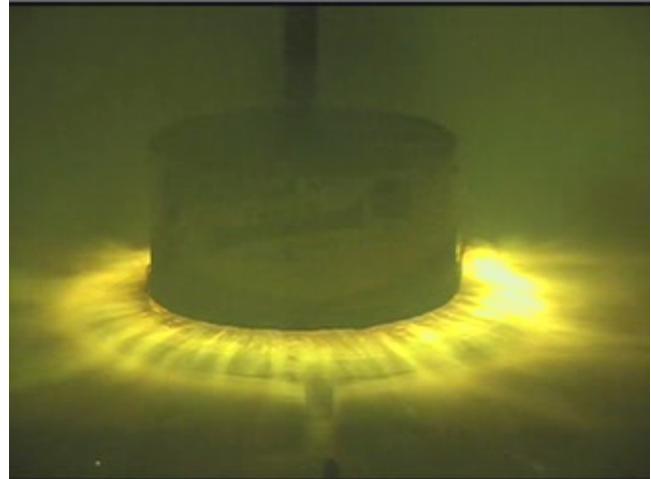
For each simulation of an Accident Scenario, there is a small probability that a fuel pellet is damaged and material is released. The release model is composed of three statistical analyses:

- Cumulative Mass Fraction
 - Distribution of plutonia particles inside pellet after impact
- Probability of Breach
 - After impact, each pellet has a probability of sustaining a crack or breach
- Fraction Release
 - Assuming breach, certain fraction of material is released

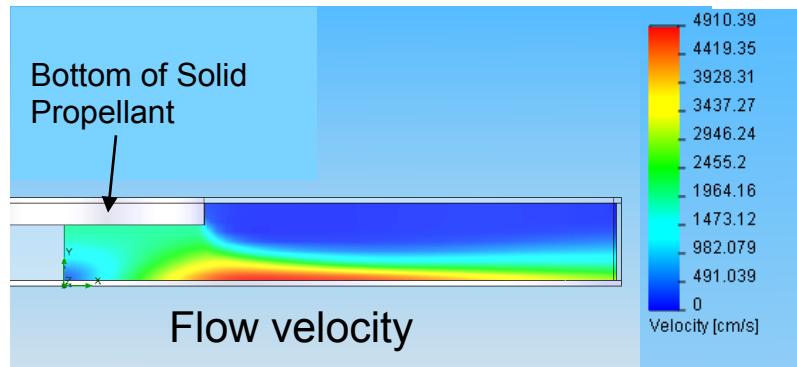


Solid Propellant Fire Modeling

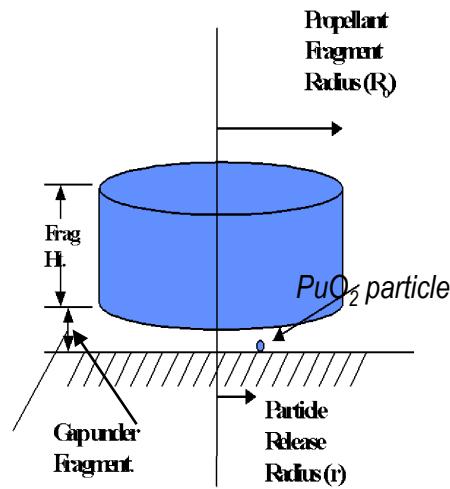
- Key Issues
 - Potential clad melt
 - Vaporization of PuO_2
 - Convective heat transfer
 - Droplet impingement
 - Does PuO_2 particle remain under propellant and vaporizing or is it transported away?



SNL fire test – 2007 (pretest 2b)

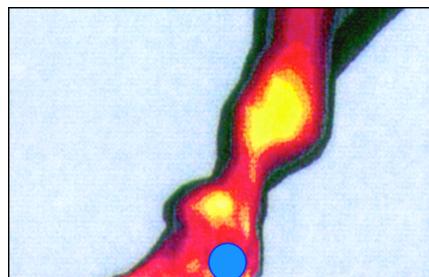
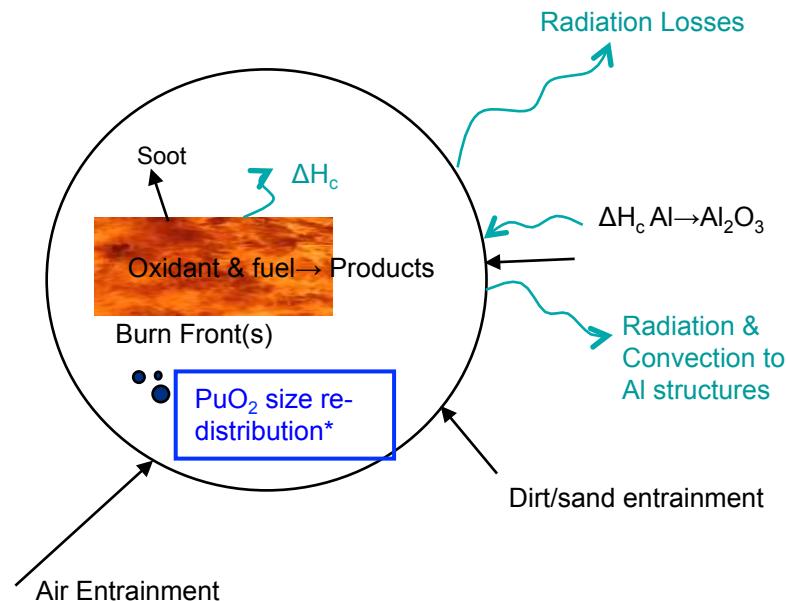


Utilizes Sandia's historic solid propellant fire testing and modeling capabilities



SFM for Liquid Propellant Fires

- Not as high a temperature as solid propellant
- Vaporizes previously released PuO_2 and condenses it into smaller, more respirable particles

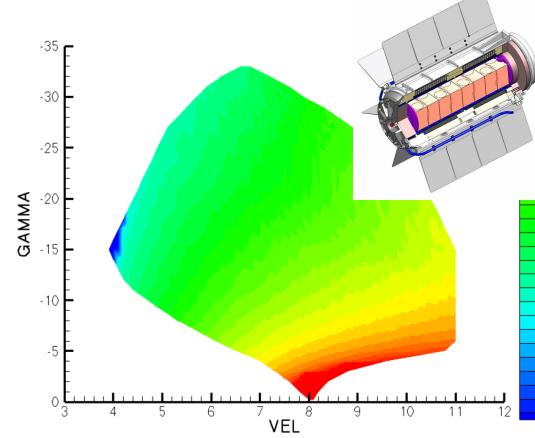


Utilizes Sandia's historic jet fuel fire testing and modeling capabilities

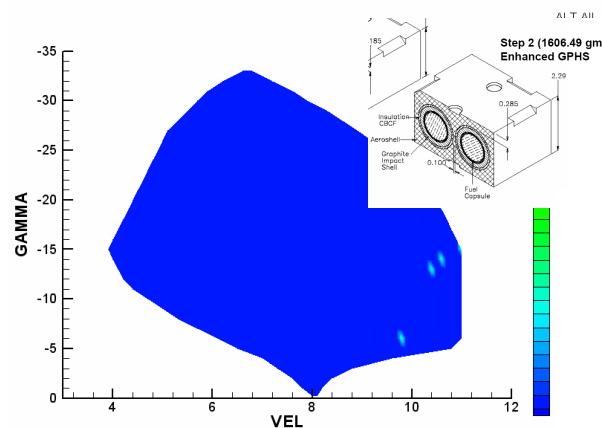
Next Generation Modeling
(VULCAN, FUEGO, CALORE)

Spacecraft Reentry

- RTG breaks up during reentry
- PuO_2 containment remains intact



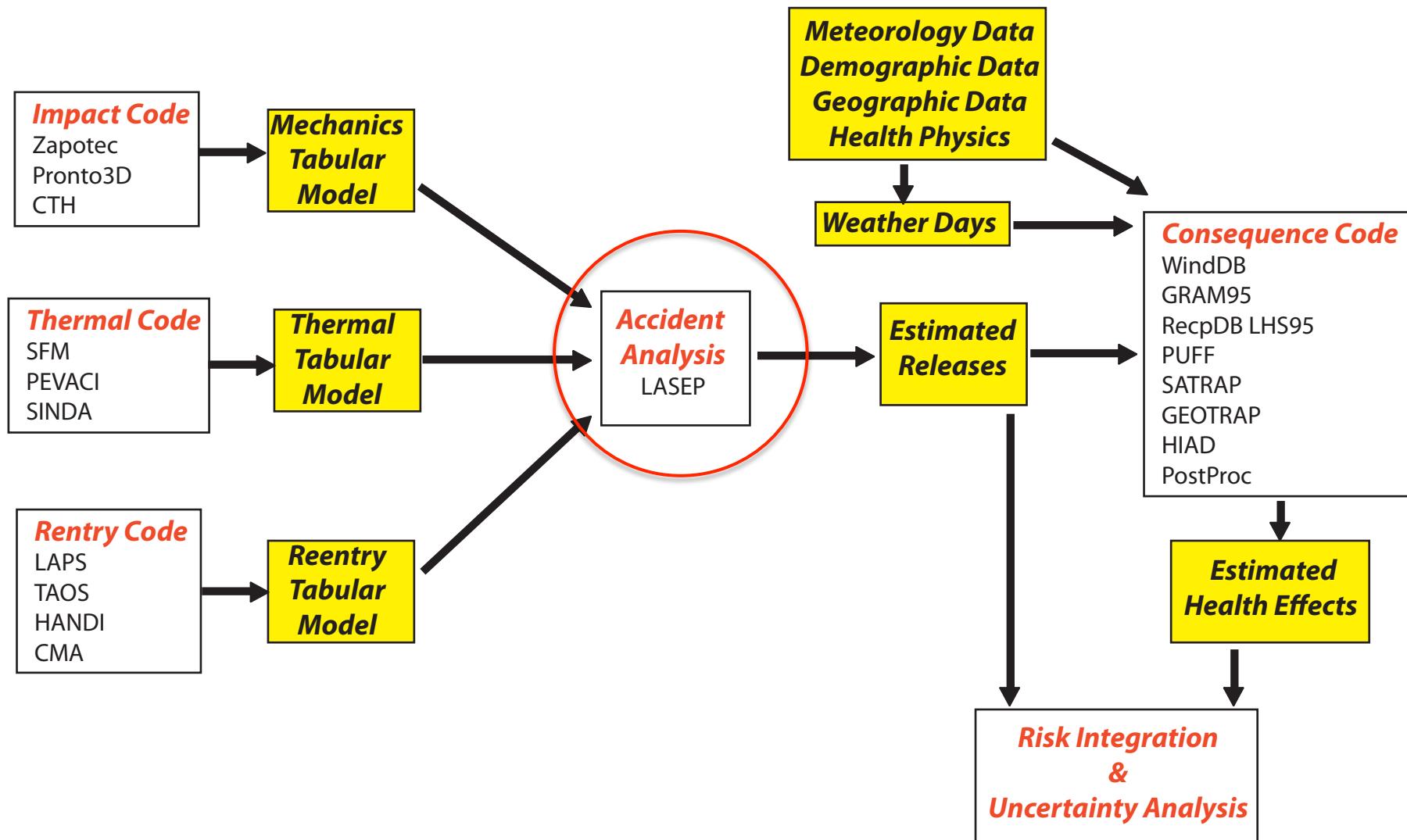
RTG Breakup



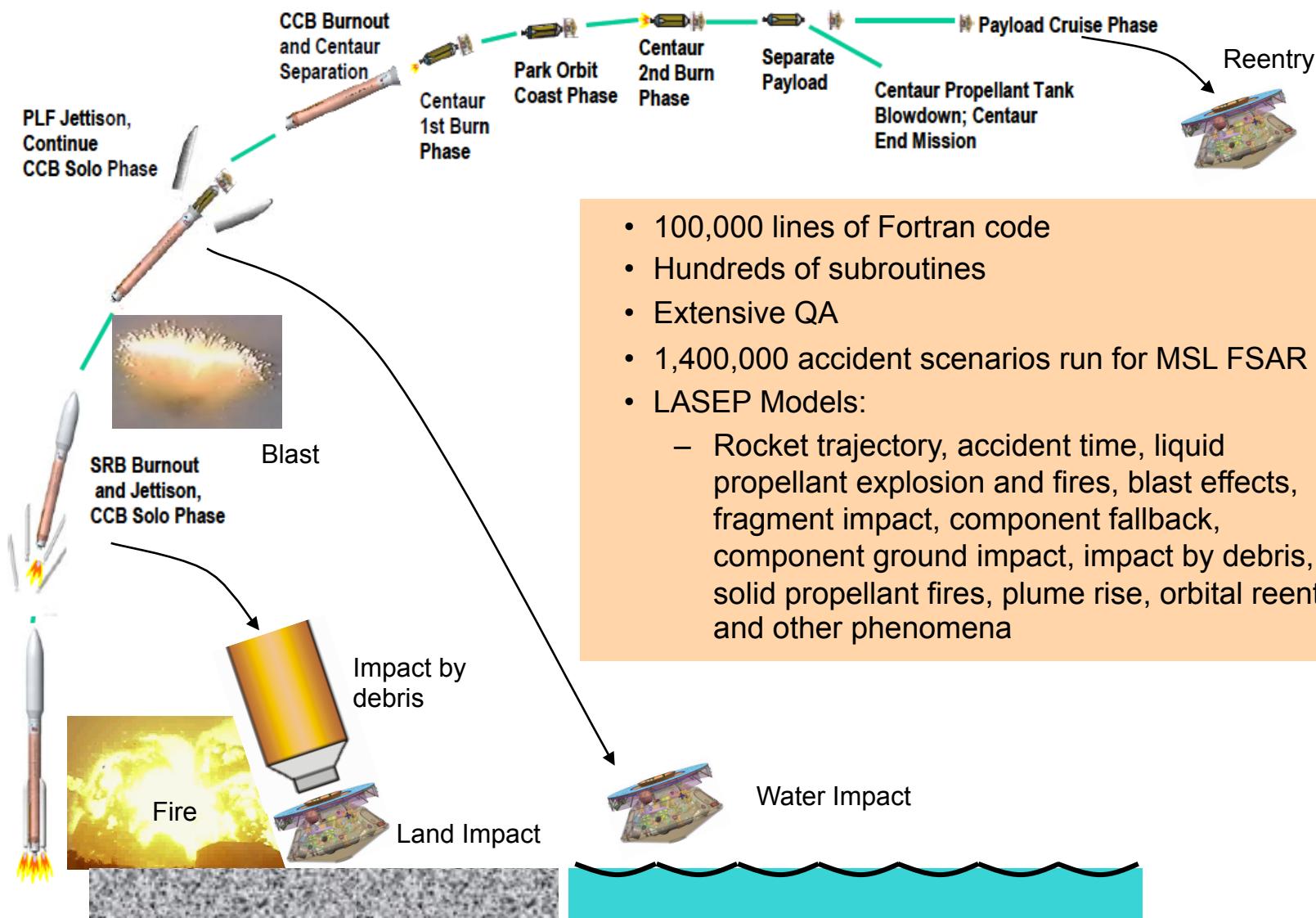
PuO_2 Containment Intact

Uses Sandia's codes developed for Reentry Vehicle modeling

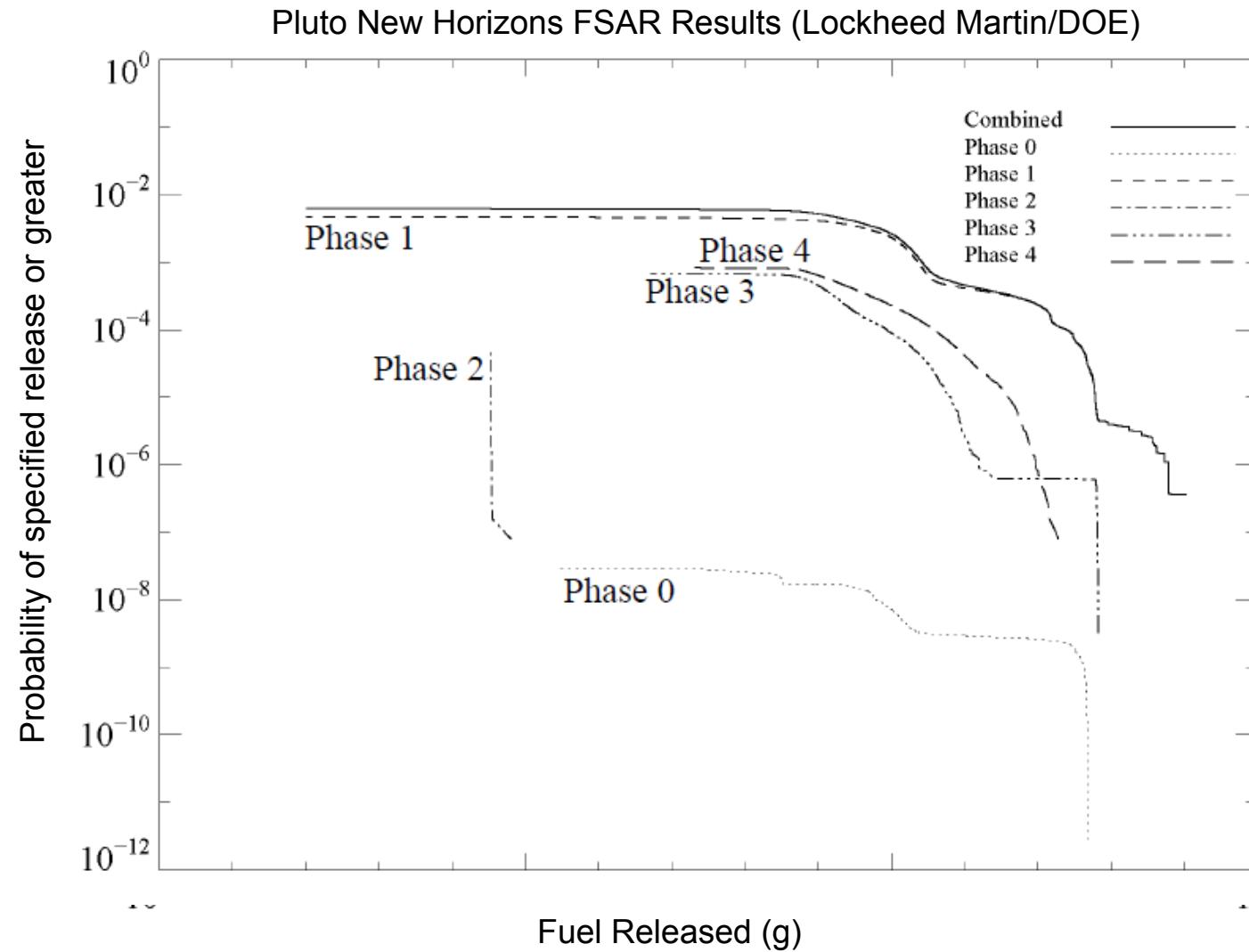
Flow of Uncertainty



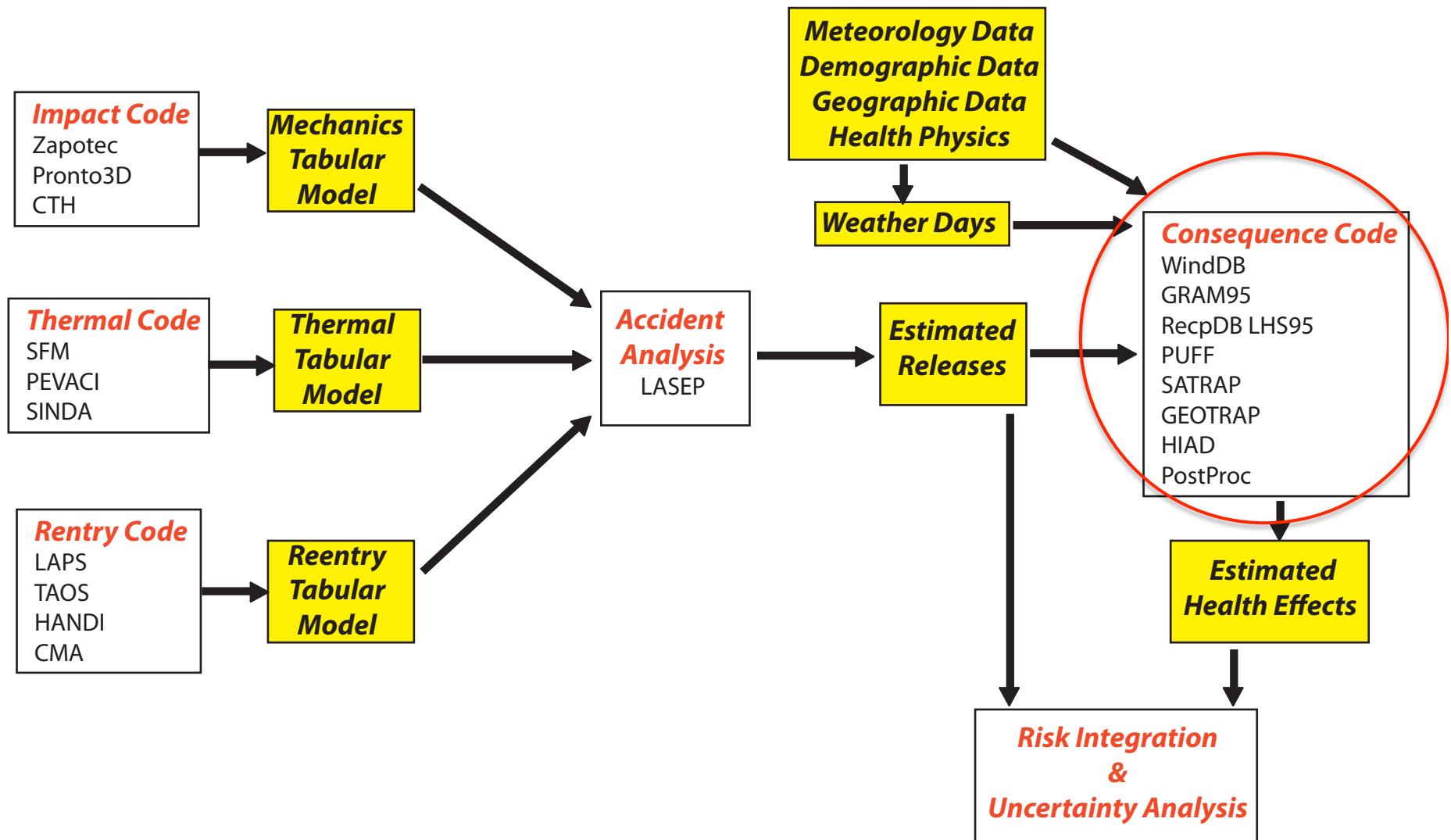
Launch Accident Analysis (LASEP)



PuO_2 Release Probabilities (Source Term)

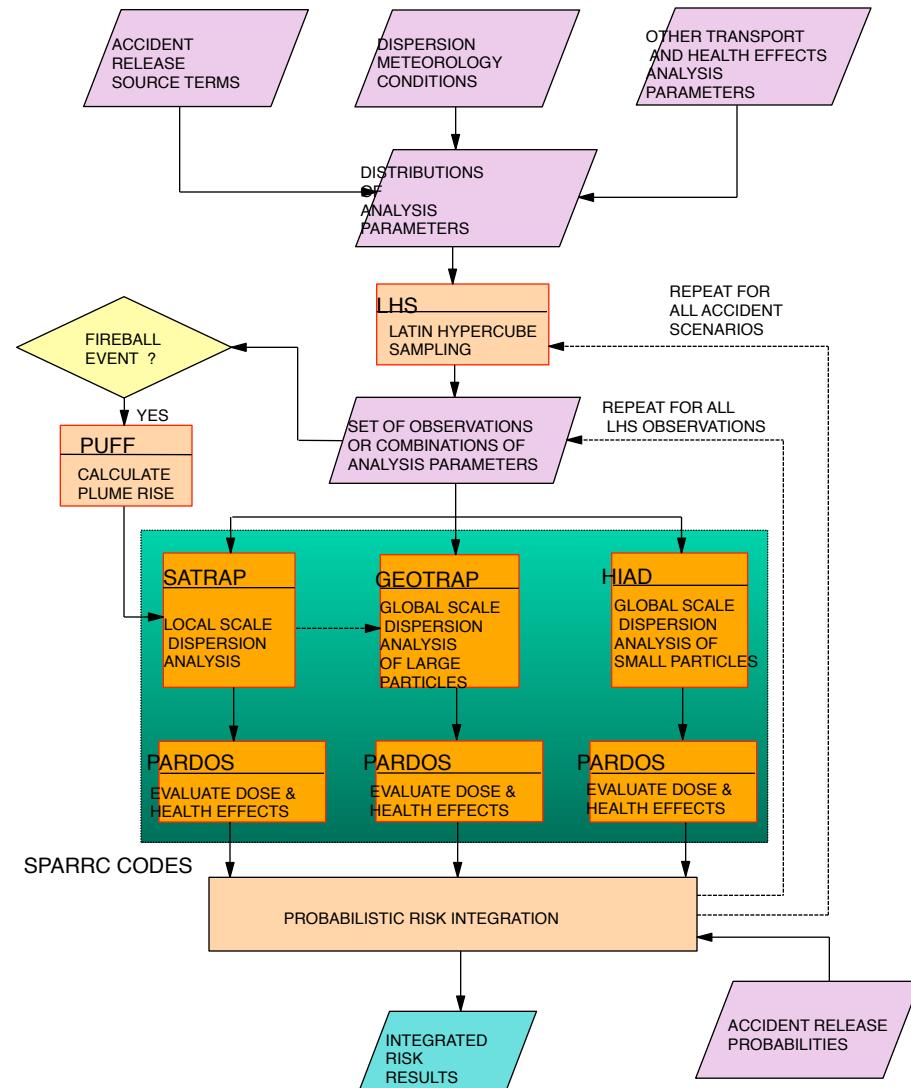


Flow of Uncertainty



Consequence Modeling Approach

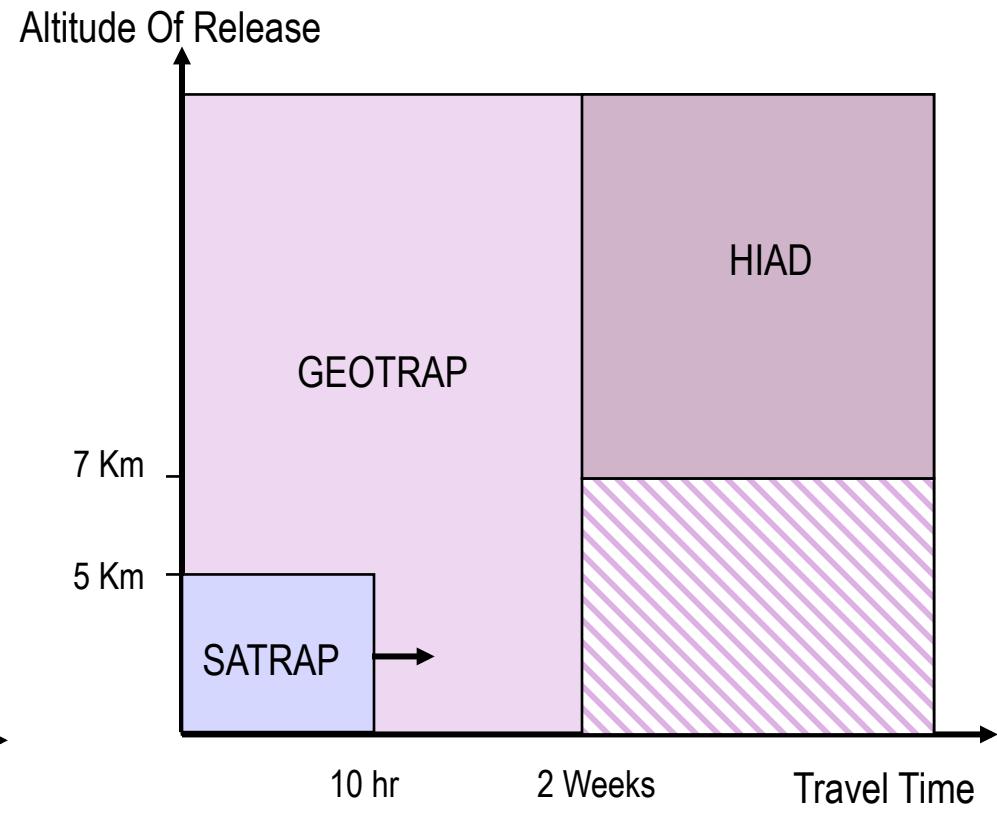
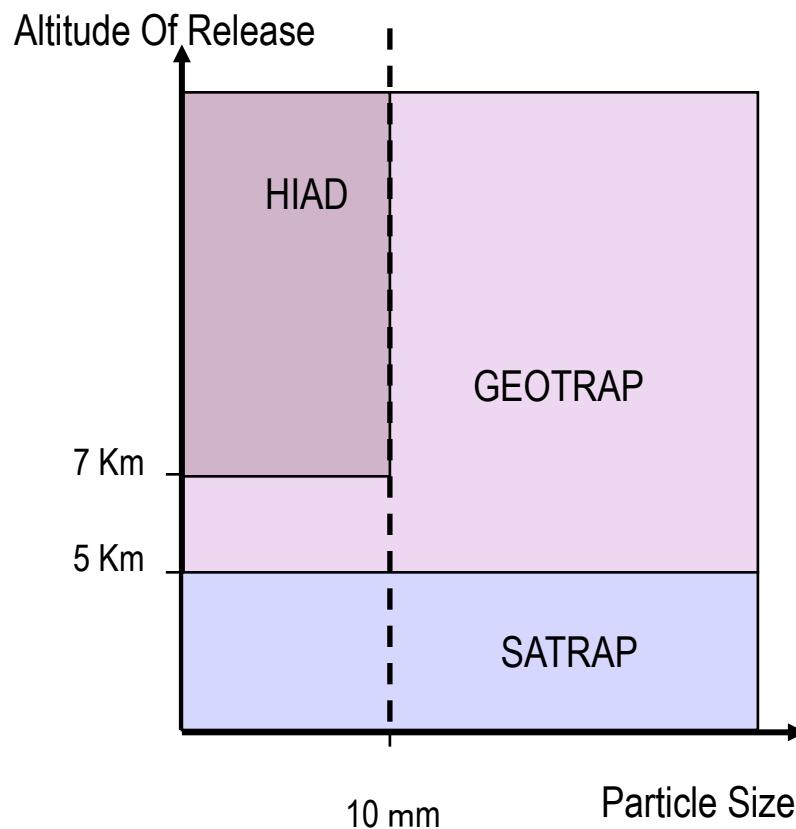
- Source terms from LASEP
- Meteorology for launch window for years 1999-2005
- Plume rise calculated by PUFF
- Atmospheric transport and dispersion calculated by SPARRC
- Doses and health effects calculated by PARDOS module with new DCFs



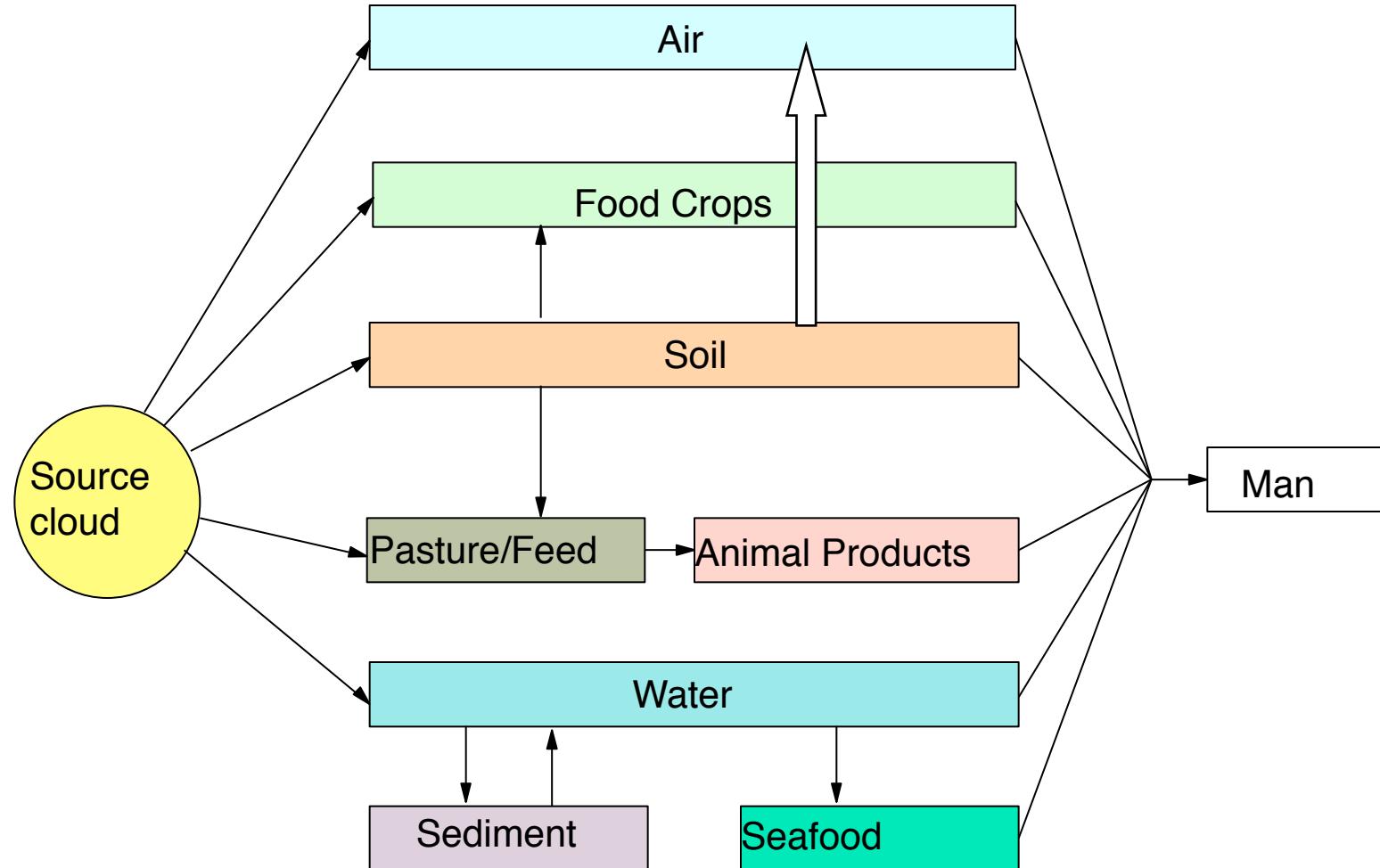
SPARRC Tool

Initial analytical tool selected by altitude of release and particle size

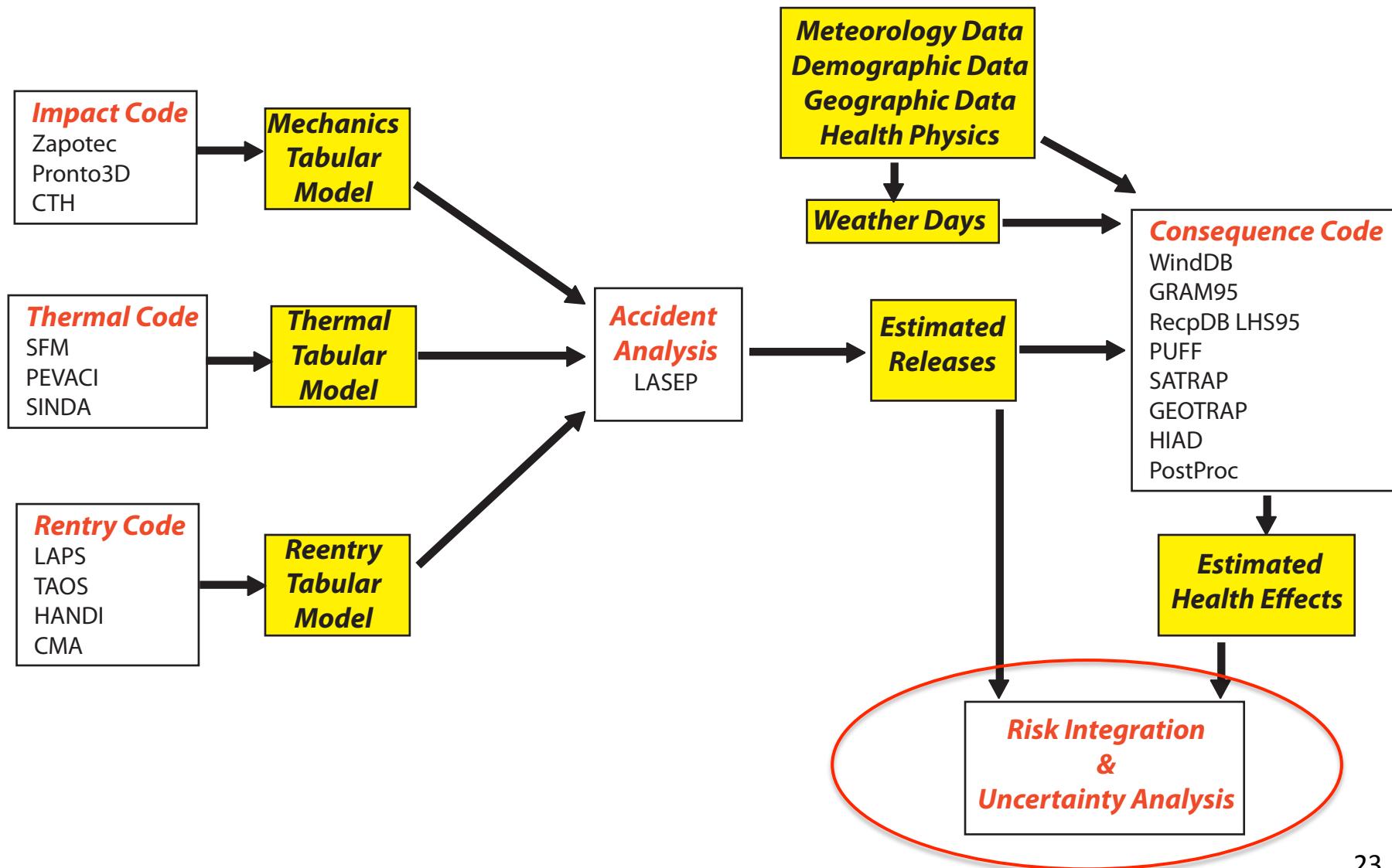
As accident evolves, the interaction between analysis tools is necessary.



PARDOS – Exposure Pathways



Flow of Uncertainty



Risk Analysis

- Risk results will be reported by:
 - Representative Accident Scenario (RAS)
 - Mission Phases: pre-launch, low altitude, high altitude, suborbital reentry, orbital reentry
 - Overall Mission
- Released Source Terms
- 50 year Health Effects
- Maximum Individual Dose
- Land Contamination at selected levels

Risk Characterization given Scenario

- Risk defined:

$$Risk = \Pr\{Health\ Effect > c_i \mid release\ characteristics\} \Pr\{release \mid accident\} \Pr\{accident\}$$

- $\Pr\{HE = c_i \mid release\}$ is provided by SPARRC
- $\Pr\{release \mid accident\}$ is output by LASEP
 - Between 196-256 random variables
- $\Pr\{accident\}$ is provided by NASA
- Risk uncertainty intervals
 - Estimated using MCMC methods



Uncertainty in Risk Characterization



- Goal of risk analysis is to characterize the underlying probability of specific consequences
 - Complimentary cumulative distribution function (CCDF)
 - Uncertainty bands about CCDF (5%, 50%, 95%)
- Want our analysis to not be dominated by assumptions regarding the underlying distribution functions: non-parametric analysis is therefore preferred
- Since we are interested in probabilistic characterization of uncertainty we are using a Bayesian approach
 - Non-parametric Bayes? Given the distribution assumptions typically required for a Bayesian analysis this would appear to be a misnomer...
 - In reality we will assume a distribution with an infinite number of parameters to approximate the CCDF (“... a point in every direction is the same as no point at all.”)

Non-parametric Bayesian Analysis



- Recall that for a Fourier series we approximate a function with an infinite sequence of basis functions:

$$f(x) = \sum_{n=1}^{\infty} A_n \sin(nt)$$

- For a non-parametric Bayesian analysis we will be using an infinite sequence to approximate the CCDF:

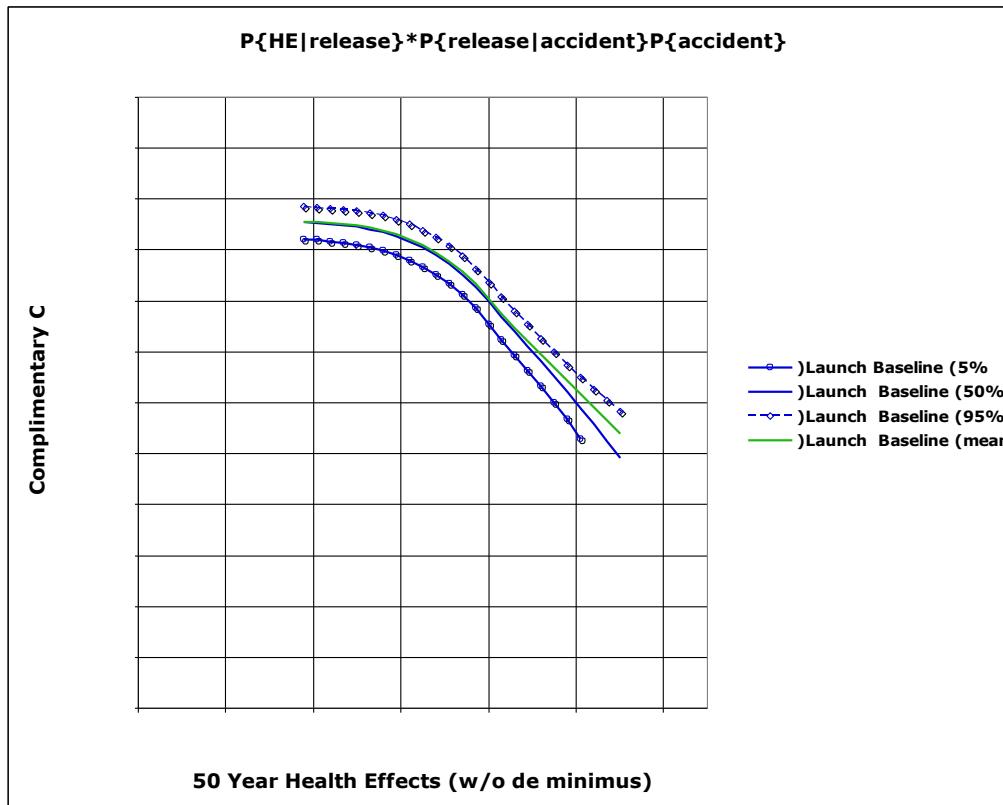
$$f(x \mid \bar{\theta}) = \sum_{i=1}^{\infty} p_i \cdot g_i(x \mid \bar{\theta})$$

- Instead of a trigonometric function, a probability density function is used.
- Potentially, each point in our data (2000 points) could come from a different distribution.
- In reality to avoid overfitting, this series is truncated to the first few significant contributors depending on the physical characteristics of the underlying process.

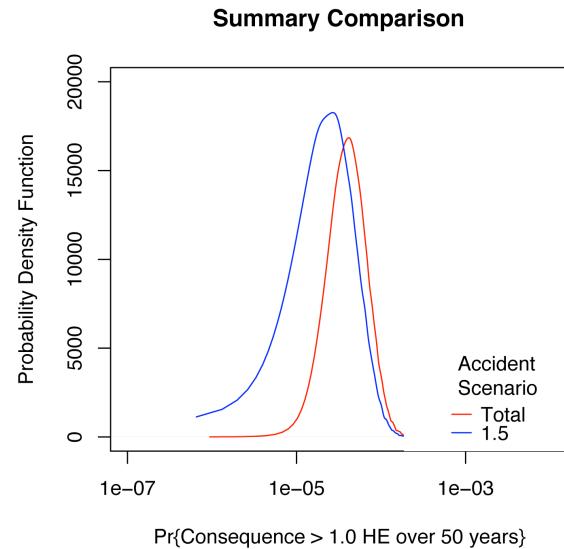
Launch Risk

Using this non-parametric Bayesian approach we can combine the CDFs from each Accident Scenario and from each launch phase.

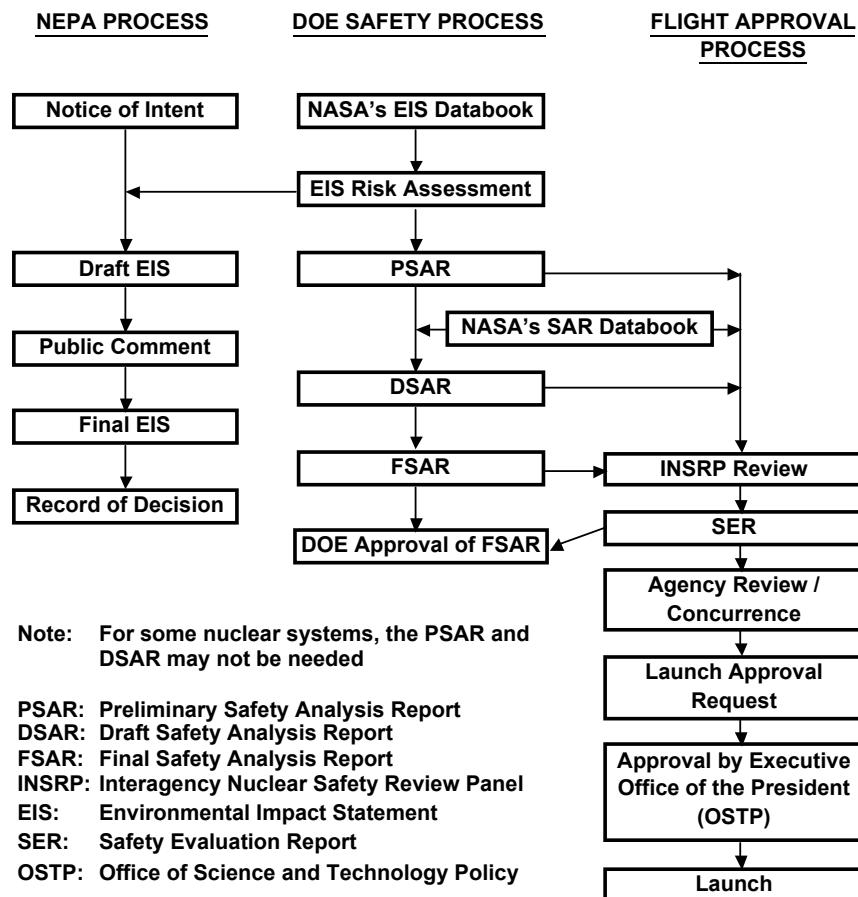
The result is a complete characterization of the launch risk and the capability to identify which accident scenario is the major contributor to risk.



Sensitivity Analysis



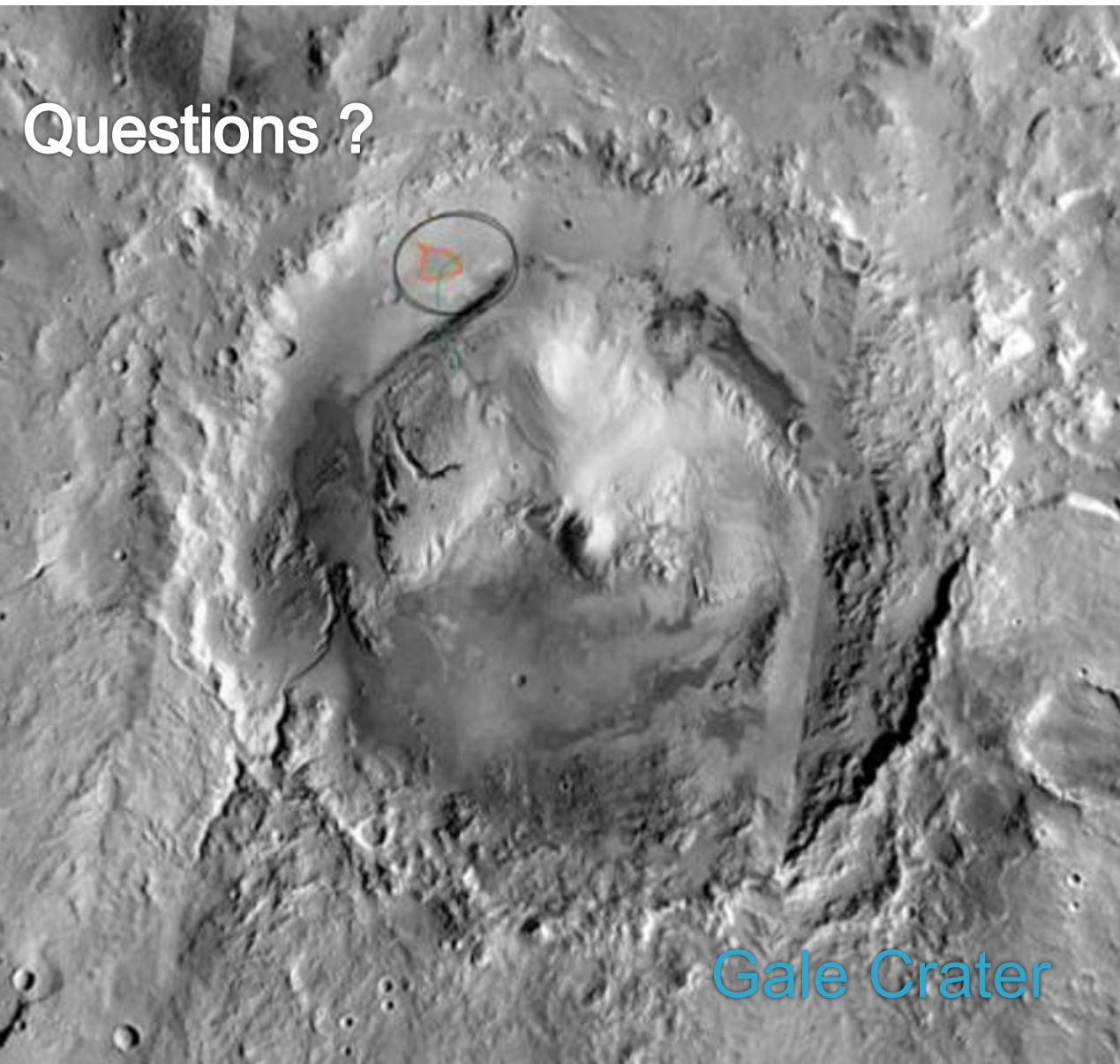
Launch Approval Process



The risk analysis goes through a series of extensive technical reviews by the INSRP panel.

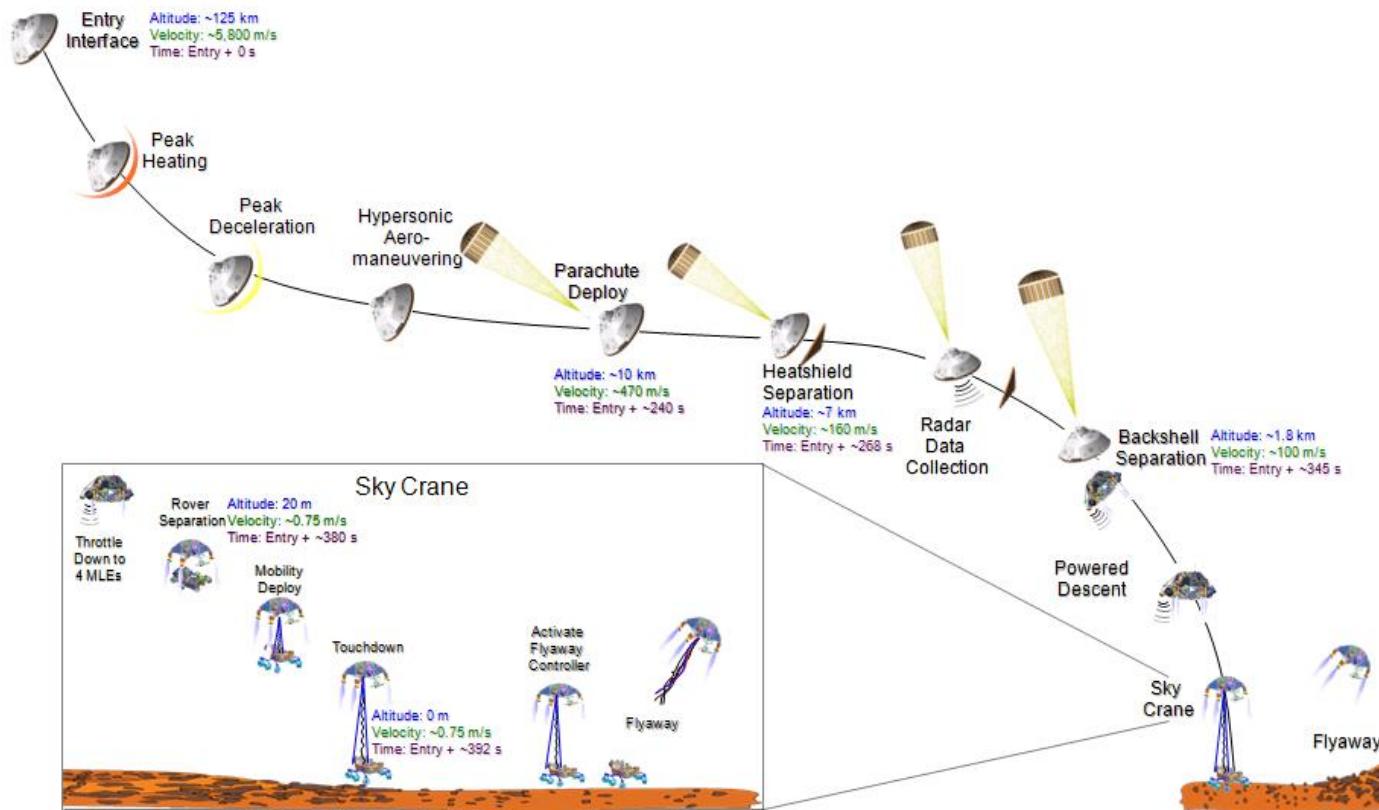
The FSAR took about 3 years to complete and is updated as design changes are made and new data becomes available.

The recommendations from INSRP and the final FSAR are presented to OSTP for final review and approval.



Backup slides

Mission Time Line



Cumulative Mass Fraction

- Data is collected for a number of pellets and the fraction of the material falling into each bin, f_i , is recorded. Since $\sum_i f_i = 1$ traditional statistical methods can not be employed.
- The additive logratio transformation is therefore applied to the data

$$y = \left[\log\left(\frac{f_1}{f_{21}}\right), \dots, \log\left(\frac{f_{n-1}}{f_{21}}\right) \right],$$

- Define: E to the internal strain energy of the pellet after impact and S_j to the maximum particle size in bin j
- Assume that the expected logratio of the fraction of particles in the bins is a (log)linear function of strain energy and maximum bin size with a changepoint C at 10 microns:

$$\varepsilon_j = \alpha_1 + \alpha_2 E + C S_j$$

$$g(y | \varepsilon, \tau_y) \sim N(\varepsilon, \tau_y)$$

$$C = \begin{cases} \beta_1 & S_j \leq 10 \mu \\ \beta_2 & S_j > 10 \mu \end{cases}$$

- Finally, assume that the model parameters are uncertain and prior to incorporation of any data, the parameters have the following statistical characteristics

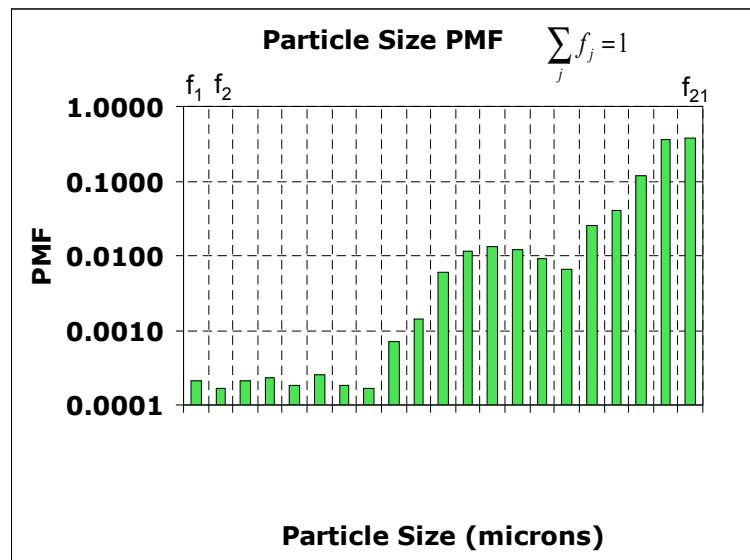
$$\beta_1 \sim N(0, 0.001)$$

$$\alpha_1 \sim N(0, 0.001)$$

$$\alpha_2 \sim N(0, 0.001)$$

$$\beta_2 \sim N(0, 0.001)$$

$$\tau_y \sim \text{Gamma}(0.01, 0.0001)$$



Probability of Breach

- After impact, each fueled clad has a certain probability of sustaining a crack or a breach. The likelihood of a breach occurring is a function of the relative strain energy, S , imparted on the clad.
- Assume that the probability of breach is a Bernoulli distributed random variable conditioned on the parameter p :

$$y | p = \begin{cases} 1 & \text{breach of fueled clad} \\ 0 & \text{no breach} \end{cases}$$

- Define s to be the imparted relative strain energy, μ_s to be the mean of the observed strain energies. A logistic regression can then be performed to determine the parameters of the relationship: $\text{logit}(p) = \beta_1 + \beta_2(s - \mu_s)$
- Since the model parameters are unknown prior to incorporating any data, the parameters are assumed to have zero mean and low precision (wide variance):

$$\beta_1 \sim N(0, 0.001)$$

$$\beta_2 \sim N(0, 0.001)$$

- Finally, a Data Augmentation Approach (DAP) was used to incorporate expert judgment gained from simulation data.

Fractional Release

- When a fueled clad is breached, unless the clad is completely severed, only a fraction of the material in the clad is actually released to the environment. The intent of the Fraction Release model is to characterize the actual fraction of the material released in the event of a breach
- There is roughly a linear (log-log) relationship between the total material released and the breach area. In addition, there is roughly a linear (log-log) relationship between the material less than 10 microns and the breach area.

$$g(f_{r_t} | \varepsilon_t, \tau_t) \sim N(\varepsilon_t, \tau_t)$$

$$\varepsilon_t = \beta_1 + \beta_2 A$$

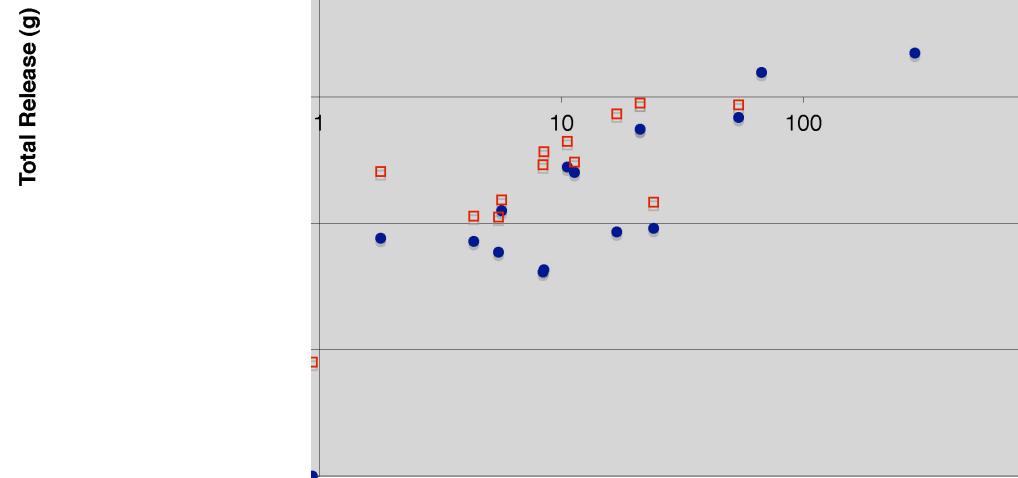
$$g(f_{r_{10}} | \varepsilon_{10}, \tau_{10}) \sim N(\varepsilon_{10}, \tau_{10})$$

$$\varepsilon_{10} = \alpha_1 + \alpha_2 A$$

$$\alpha_1, \alpha_2 \sim N(0, 0.001)$$

$$\beta_1, \beta_2 \sim N(0, 0.001)$$

$$\tau_t, \tau_{10} \sim \text{Gamma}(0.01, 0.0001)$$



Material Released versus Breach Area

DPP: Basis Function

- For MSL we will used the lognormal as the basis function $F(\cdot)$
 - Positive support (health effects)
 - Most basic
 - Simple to use
- $X \sim \text{lognormal}$ if $Y = \ln(X) \sim \text{Normal}$

$$F(x | \mu, \tau) = \sqrt{\frac{\tau}{2\pi}} \frac{1}{x} \exp\left[-\frac{\tau}{2}(\log(x) - \mu)^2\right]$$

$$G(y | \mu, \tau) \sim N(\mu, \tau)$$

$$E[Y] = \mu$$

$$V[Y] = 1/\tau$$

$$E[x] = \exp[\mu + 1/2\tau]$$

$$V[x] = \mu^2 (\exp[1/\tau] - 1)$$

DPP: Parameter Estimation

- Goal is to estimate CCDF of health effects:
 - n = number of disjoint intervals in DPP
 - $\alpha_i, i=1, \dots, n$, = weights of basis functions
 - $\mu_i, \sigma_i, i=1, \dots, n$ = parameters of each basis function
- Simplest approach is to use Markov Chain Monte Carlo technique
 - Data input are simulated health effects ($N=2000$ samples)
 - Assumptions about prior information:

$$\mu_i \sim N(\theta_i, \zeta_i)$$

$$\tau_i \sim Gamma(a_i, b_i)$$

- Assumed that the maximum number of intervals is $n \sim 10$