

Quantifying ECLSS Robustness for Deep Space Exploration

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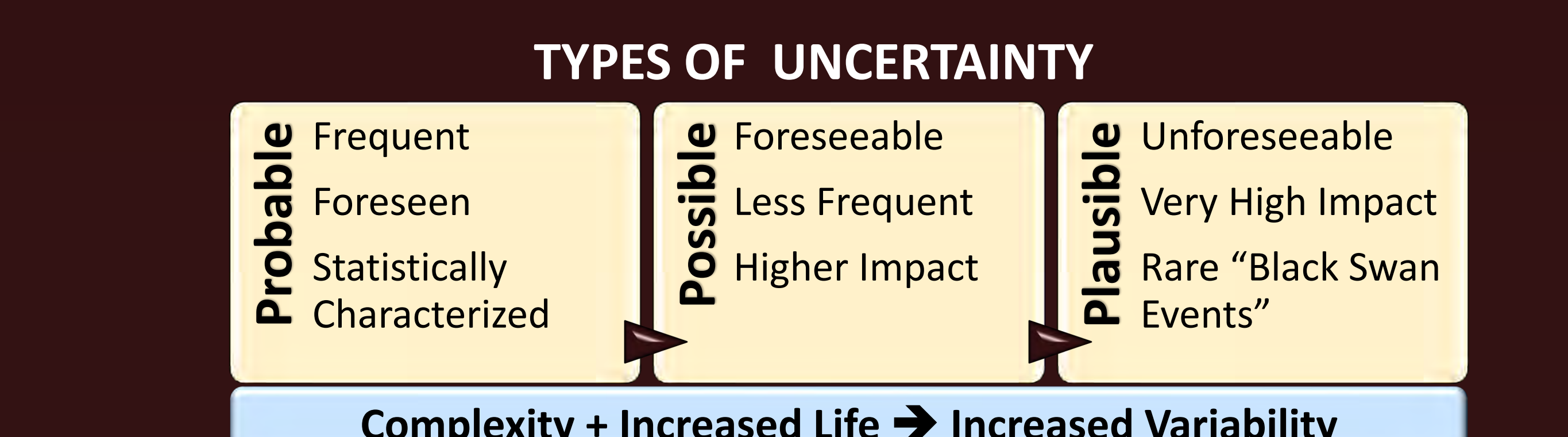
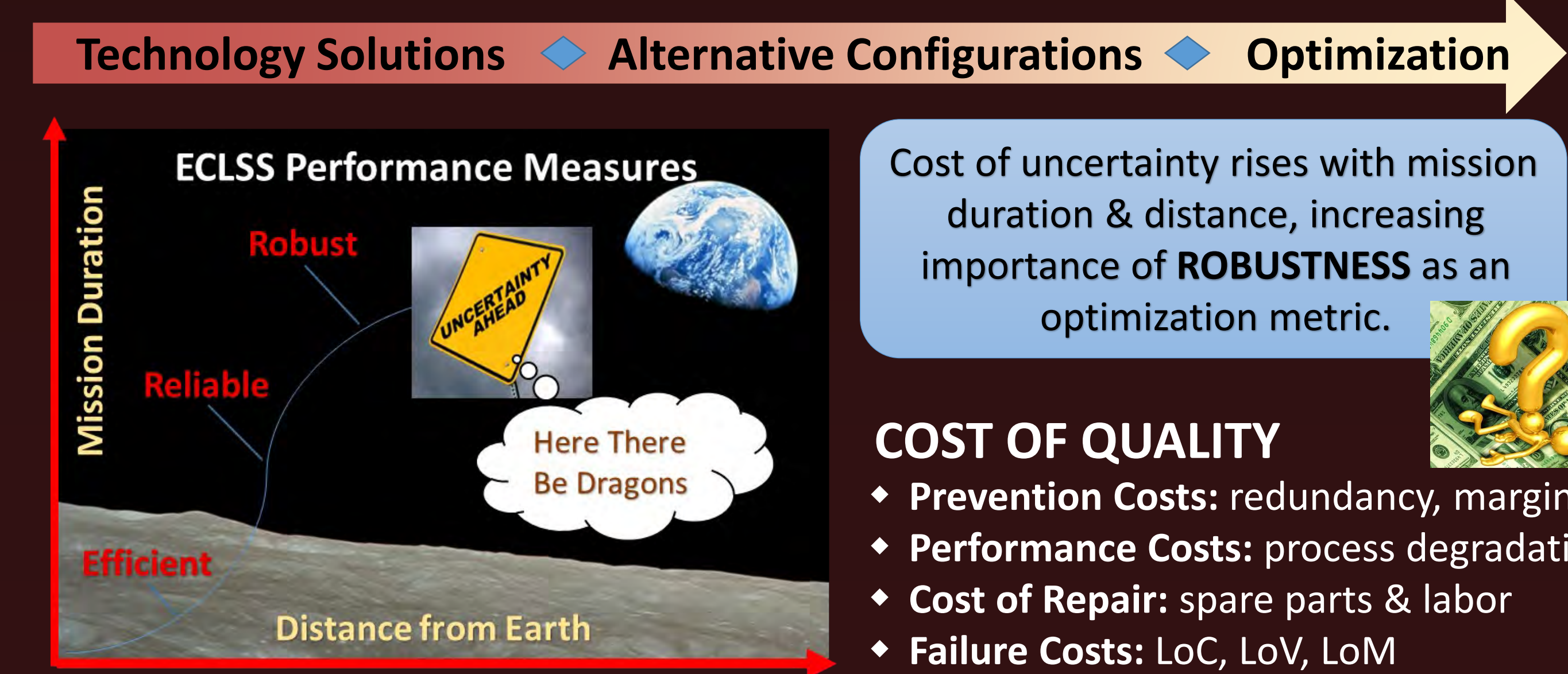
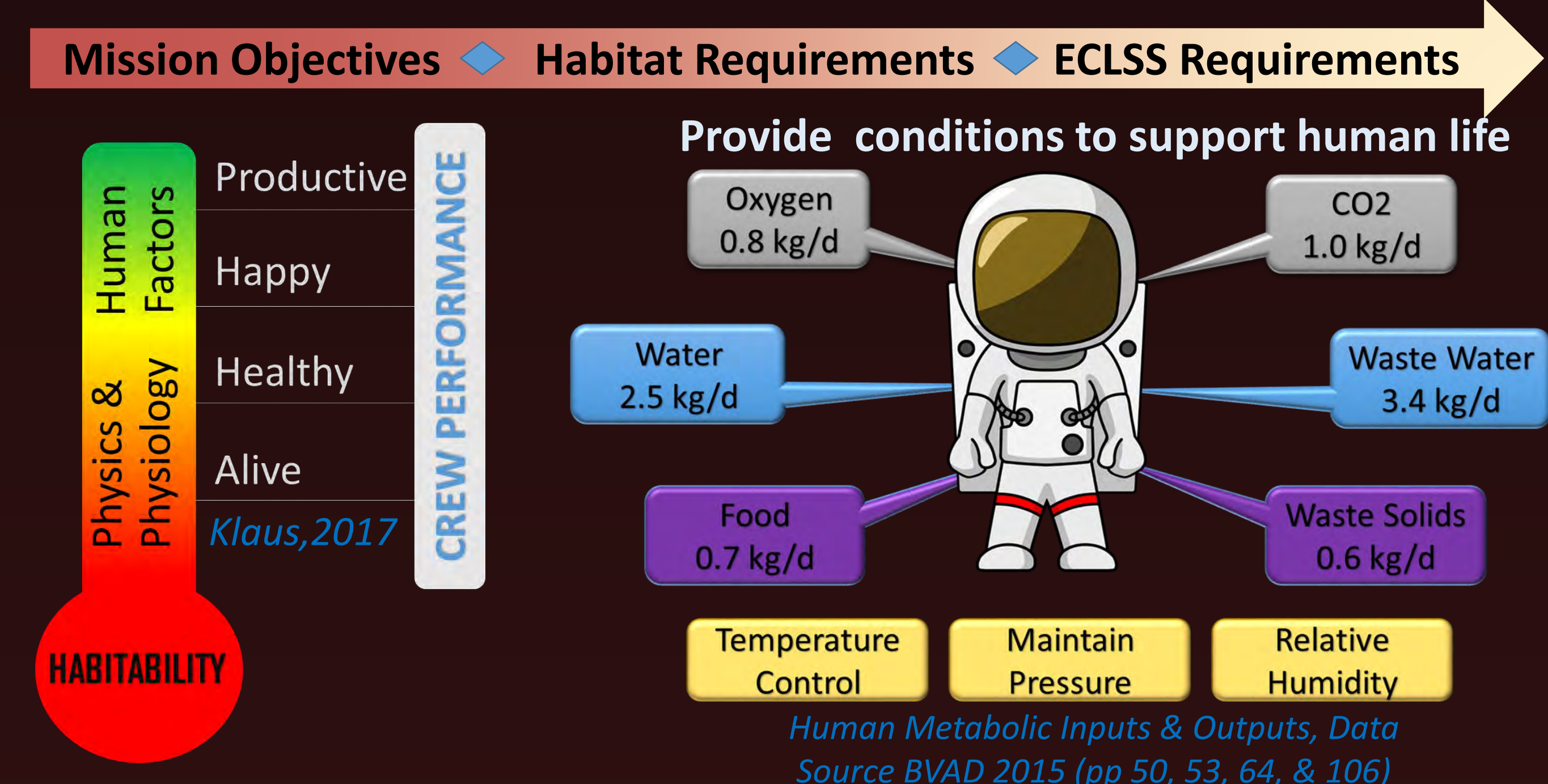
ABSTRACT

Life support system designs for human space exploration can include many different combinations of technologies. A variety of metrics might be used to determine the "best" configuration, such as efficiency (in mass, volume, or power), safety, reliability, and robustness. Mission characteristics will dictate the relative importance of these factors. For sustainable deep space exploration, as mission duration and distance from Earth increases, robustness may become the more important design criteria. The goals of this research are to define metrics and propose design practices for optimizing ECLSS robustness so that sustainable environmental control and life support systems can be realized for long term space missions.

RESEARCH OBJECTIVES

- Objective 1: Define a quantitative, measurable robustness metric for spacecraft ECLSS
- Objective 2: Provide design guidance for improving ECLSS robustness
- Objective 3: Demonstrate a methodology for assessing robustness of an ECLSS design

NEED FOR ROBUST ECLSS DESIGN



Sources of Uncertainty: Component performance, system dynamics, operating environment, mission characteristics

A ROBUST DESIGN METHODOLOGY FOR ECLSS

Robust: "Capable of performing without failure under a wide range of conditions" *Merriam-Webster*

"Often [spacecraft] systems are forced to operate under conditions which deviate significantly from ideal design conditions. A degree of how well a system performs with no appreciable degradation in performance under such conditions is measured by its robustness." *Miller et al. (2008)*

ECLSS robustness is its ability to maintain habitable conditions for crew survival and productivity over the mission lifetime under a wide range of conditions.

ECLSS robustness includes insensitivity of performance (i.e. maintaining habitability) to

- 1) Random expected failures and conditions (reliability)
- 2) Foreseen but unexpected deviations in conditions or disturbances (resilience)
- 3) Unforeseen disturbances or adverse events (survivability) *Escobar et al., 2017*

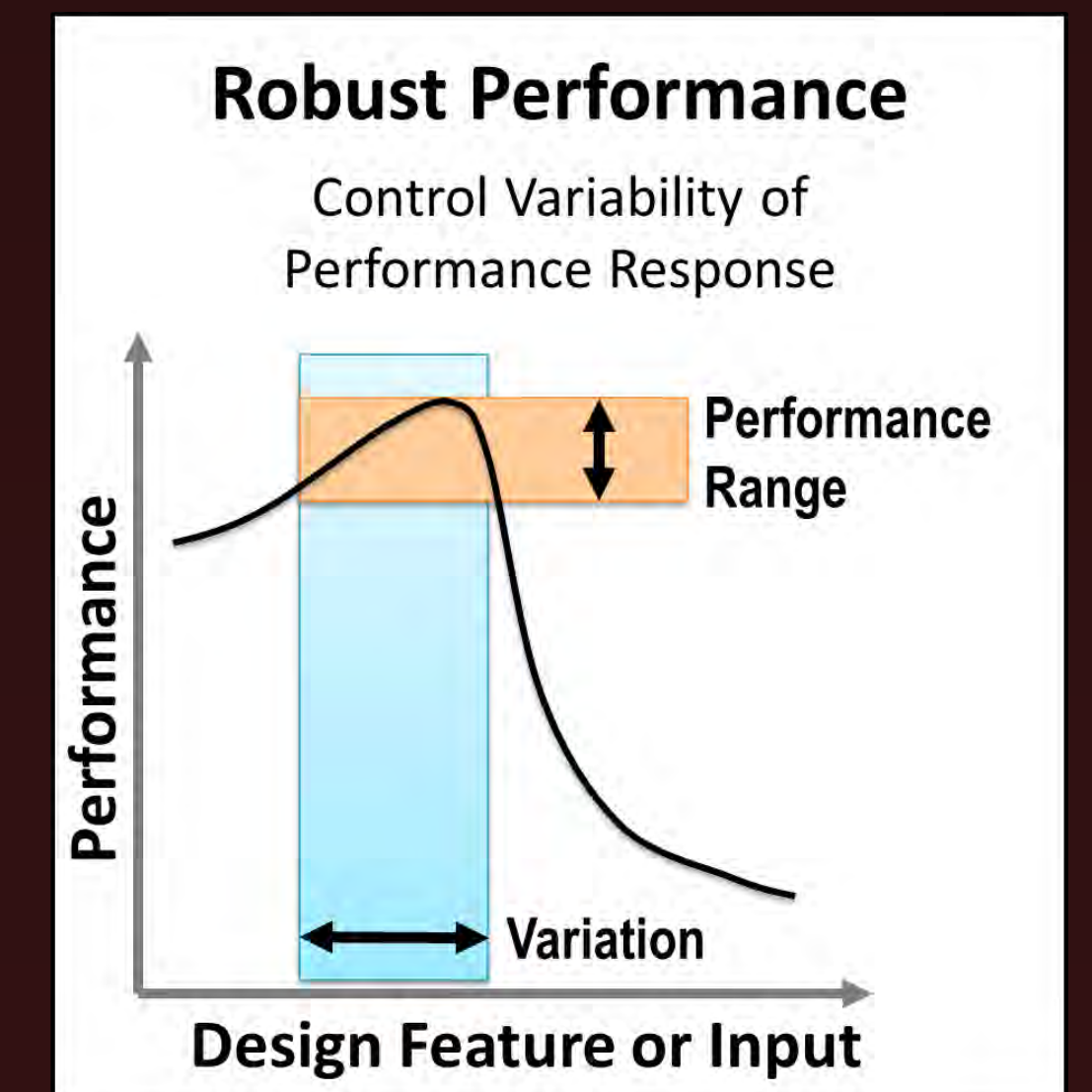


A new "robustness" metric is needed to describe system availability in off-nominal conditions, or abnormal use.

Evolution of Robust Design Methodology

Robust design practices evolved from quality engineering and industrial process control, starting with the ideas of Genichi Taguchi in Japan.

The engineering community generally agrees that variation in usage conditions or inputs imparts quality loss, and that the goal of robust design is to find control factors (i.e. design features) that reduce sensitivity to noise.



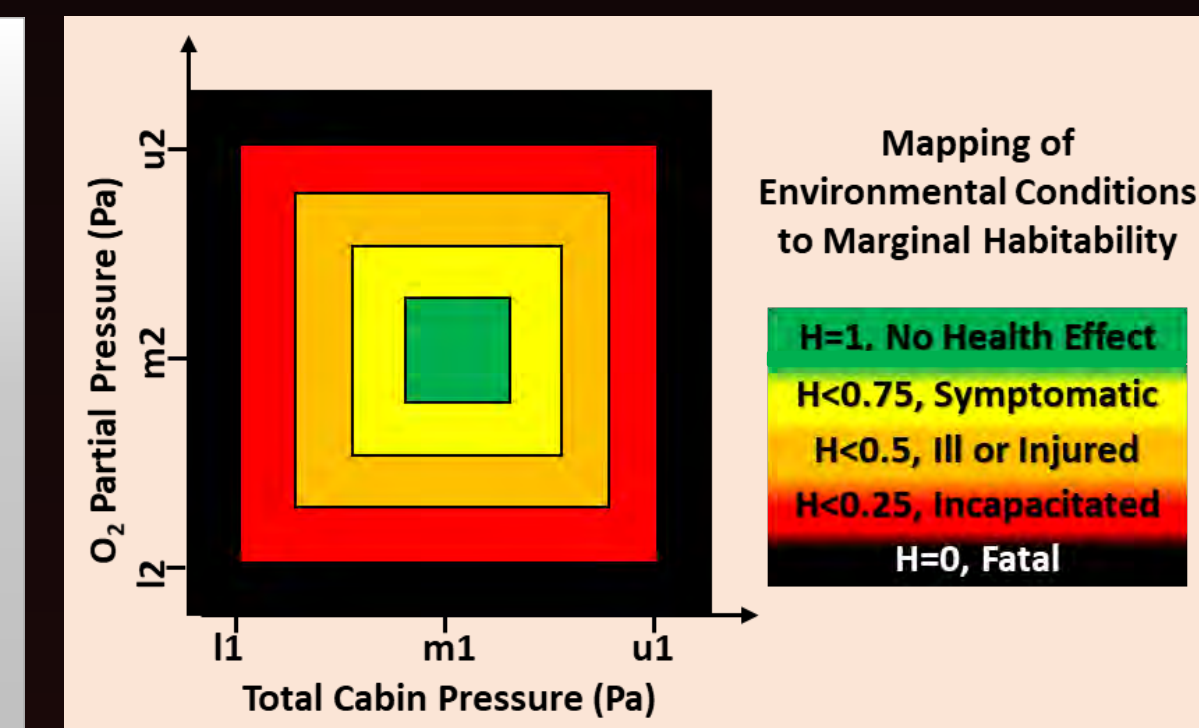
General Robust Design Methodology	Methodology for Robust ECLSS Design
1. Define key product characteristic (KPC):	Define "Habitability"
2. Identify & characterize variation sources:	Characterize ECLSS inputs, operating conditions, component reliability, etc.
3. Define or model system behavior:	Mathematical or physical ECLSS model
4. Quantify robustness of KPC given variation & system model:	Need an ECLSS robustness metric
5. Select or improve design:	Identify design features contributing to habitability loss w/ minimum cost of quality

QUANTIFYING ECLSS ROBUSTNESS

Habitability is the ECLSS Key Product Characteristic (KPC)

Potential Habitability Contributors (y_i) → Map to Utility Functions, $H_i \in [0,1]$

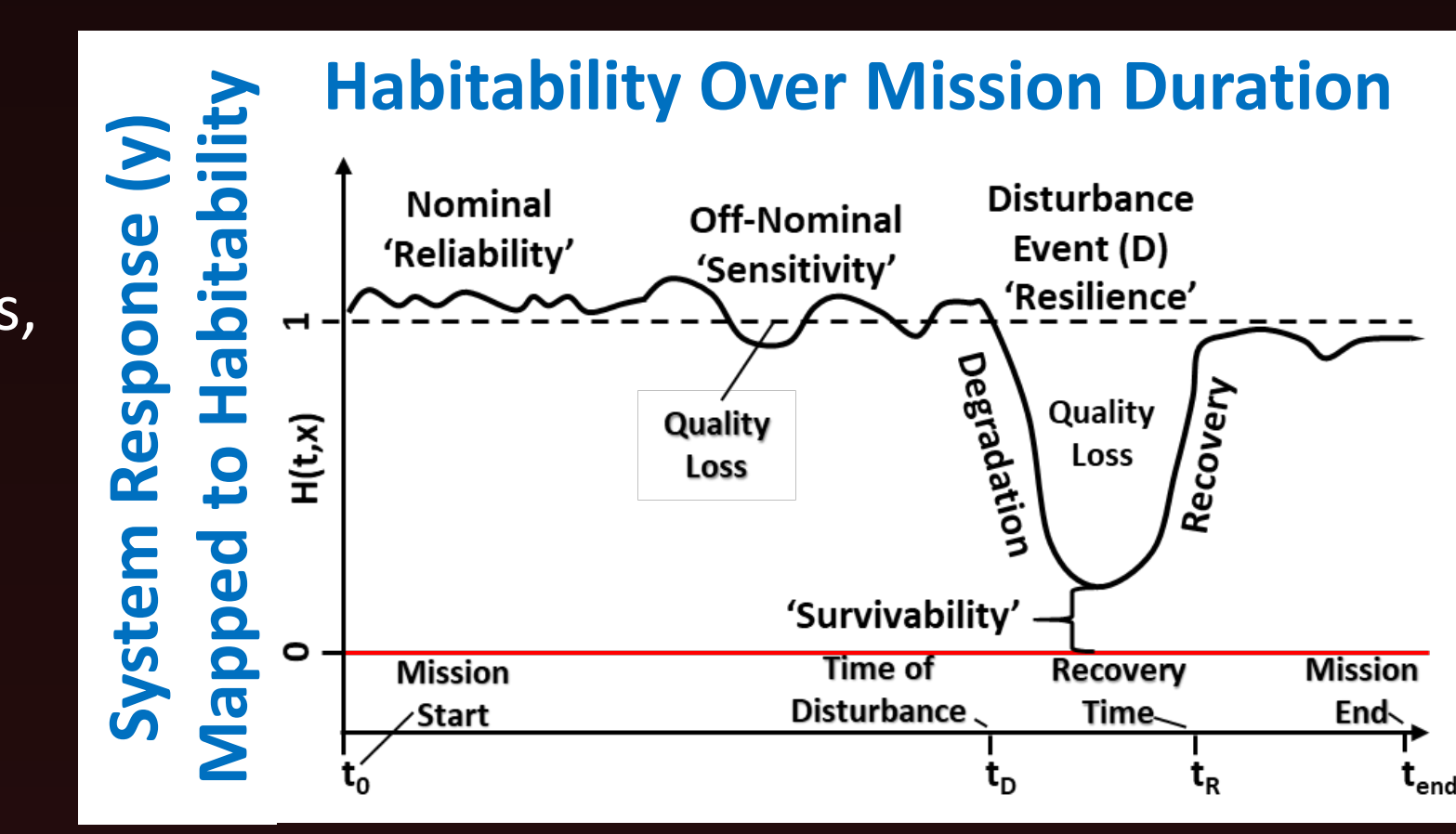
Contributors include O₂ partial pressure, CO₂ partial pressure, total cabin pressure, wet bulb temperature, food & water availability and quality, or even the presence of noxious substances.



Habitability Index Definition

1. H must be 1 when crew performance capacity is full → all H_i are equal to 1.
2. H must be 0 under any fatal conditions, i.e. when any $H_i = 0$.
3. H must be no better than any individual H_i , i.e. $H \leq \min(H_i)$.
4. The impact of H_i on H is not independent. A reduction in one H_i increases the impact of another H_i .

$$H = \prod H_i, \text{ for } i = 1, \dots, n \text{ \& } H_i \in [0,1]$$



Many Possible Robustness Metrics

1. Variance	5. Quality Loss	9. Variation Risk Priority #
2. Effective Fitness $E(y)$	6. Sensitivity ($\delta y / \delta x$)	10. Information Content (Axiomatic Design)
3. Minimax Optimization (Worst Case Philosophy)	7. Signal to Noise (Taguchi)	See Escobar et al., 2019 for details
4. Process Capability Index	8. Mean & Variance, Weighted Sum	

Taguchi's "Quality Loss" Function Accounts for Bias & Spread:

$$\text{Min } E(L) = E[k(y-m)^2] = k[(\mu-m)^2 + \sigma^2],$$

where m is target value of KPC & k is a cost factor

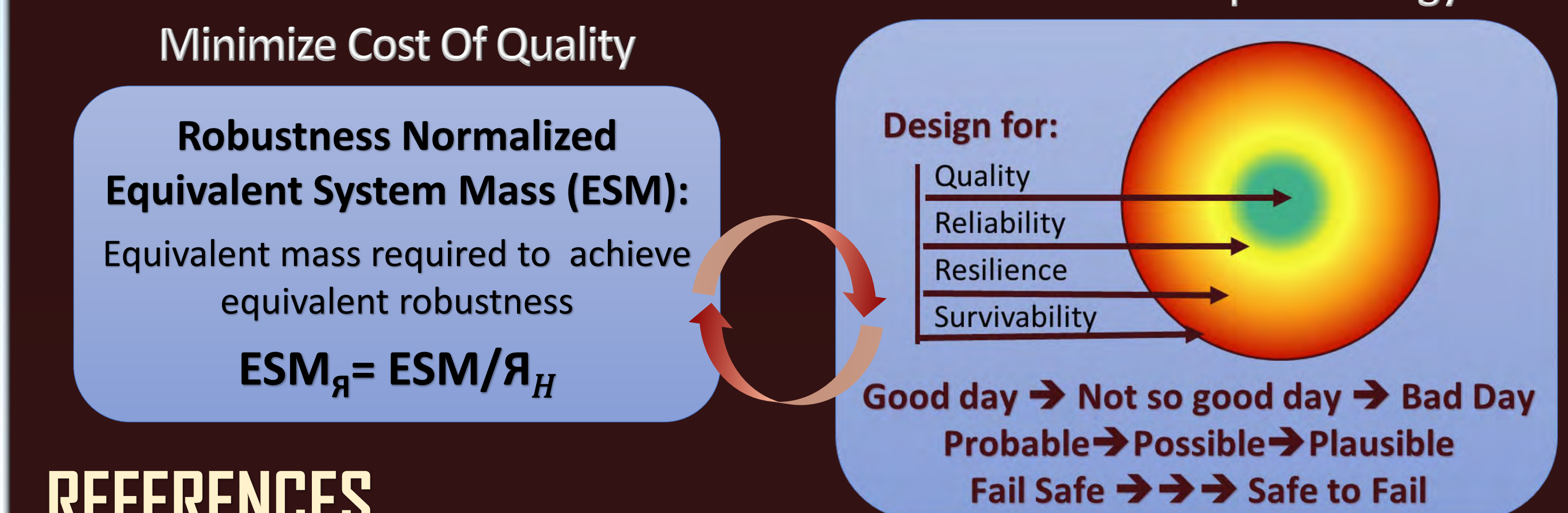
"Habitability Loss" Let $L_H = (H-1)^2$ → Expected Habitability Loss $E[L_H] = E[(H-1)^2] = [1-E(H)]^2 + \text{Var}(H)$

ECLSS Robustness:

$$R_H = 1 - \sqrt{E(L_H)} = 1 - \sqrt{[(1-E(H))^2 + \text{Var}(H)]}$$

'bias' 'spread'

IMPROVING ECLSS ROBUSTNESS



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- Miller, J., Leggett, J., and Kramer-White, J. "Design Development Test and Evaluation (DDTE) Considerations for Safe and Reliable Human Rated Spacecraft Systems," NASA/TM-2008-215126/Vol II, 2008.