34th Annual INCOSE international symposium

hybrid event

Dublin, Ireland
July 2 - 6, 2024

Gregory S. Parnell, Ph.D., CSEP

Eric Specking, Ph.D., CSEP

Randy Buchanan, Ph.D.

Using Systems Engineering and Decision Analysis in Descriptive, Predictive, and Prescriptive Analytics

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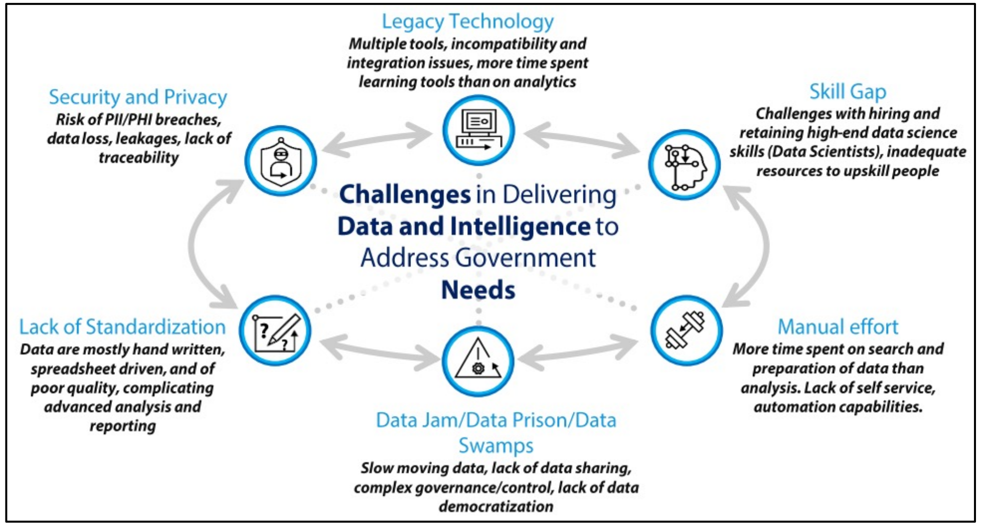
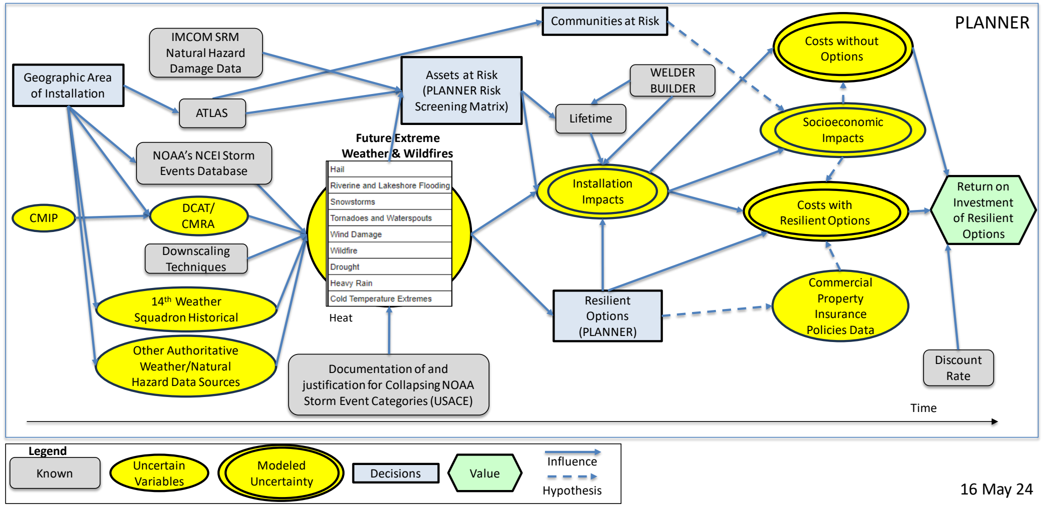
BLUF

Data Analytics Challenges in Public Sector

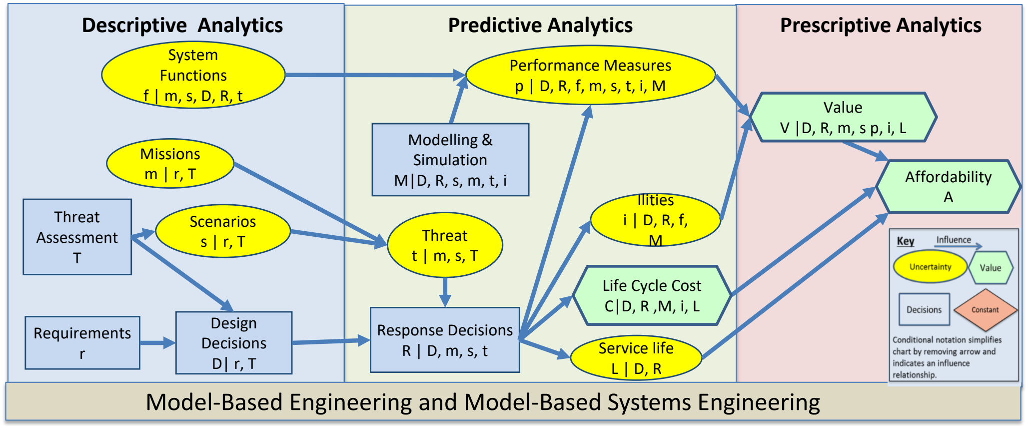


Decision Framing Tools: Influence Diagrams

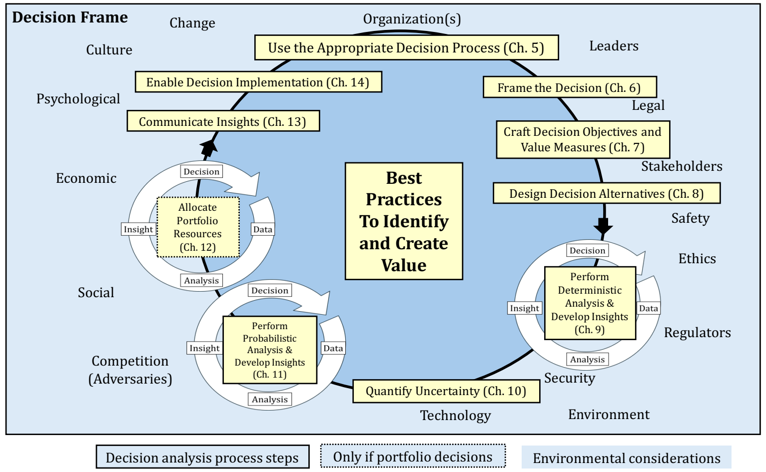


16 May 24

Data Science, Analytics and Decision Analysis



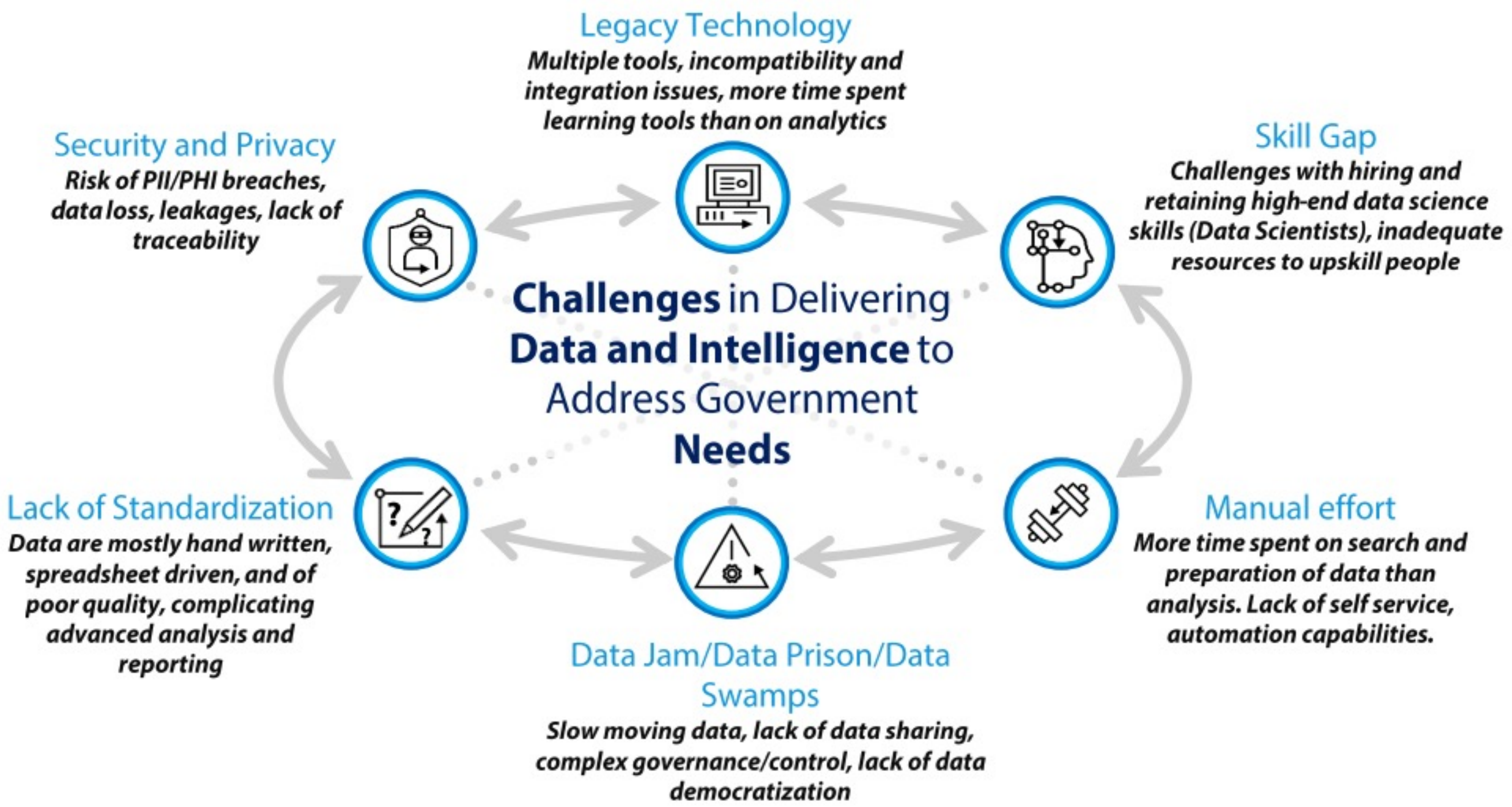
Integrate Data Analytics and Decision Analysis



Parnell, G. S., Bresnick, T. A., Tani, S. N., Johnson, E. R., and Specking E. A., **Handbook of Decision Analysis**, Wiley & Sons, Inc. Operations Research/Management Science Handbook Series, **2nd Edition**, 2025

DISTRIBUTION A. Approved for public release: distribution unlimited.

Data Analytics Challenges in Public Sector



https://www.infosyspublicservices.com/offerings/data-analytics/overview.html

Why Analytics Projects Fail

1. Unclear project goals
2. Inaccurate or unreliable data
3. Lack of skilled resources
4. Insufficient stakeholder buy-in
5. Failure to operationalize insights

https://wavicledata.com/blog/why-data-analytics-projects-fail-and-how-to-overcome-common-challenges

Parnell, G., Specking, E., Buchanan, R., "Decision Analytics: Using Decision Analysis in Analytics Projects," INCOSE IS, Dublin, Ireland, 2-6 July 2024

Overview

- Research Team
- Research Scope
- Data Analytics Perspective
- Systems Engineering Perspective
- Decision Analysis Perspective
- Five Research Projects
- Summary

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THE WEATHER-CLIMATE INTELLIGENCE TEAM

U.S. ARMY

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Electrical/Computer Engineer and Physicist
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ERDC ITL

Su Wolters
PLANNER
Program Manager
ERDC EL

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Civil Engineer
Infrastructure Resilience
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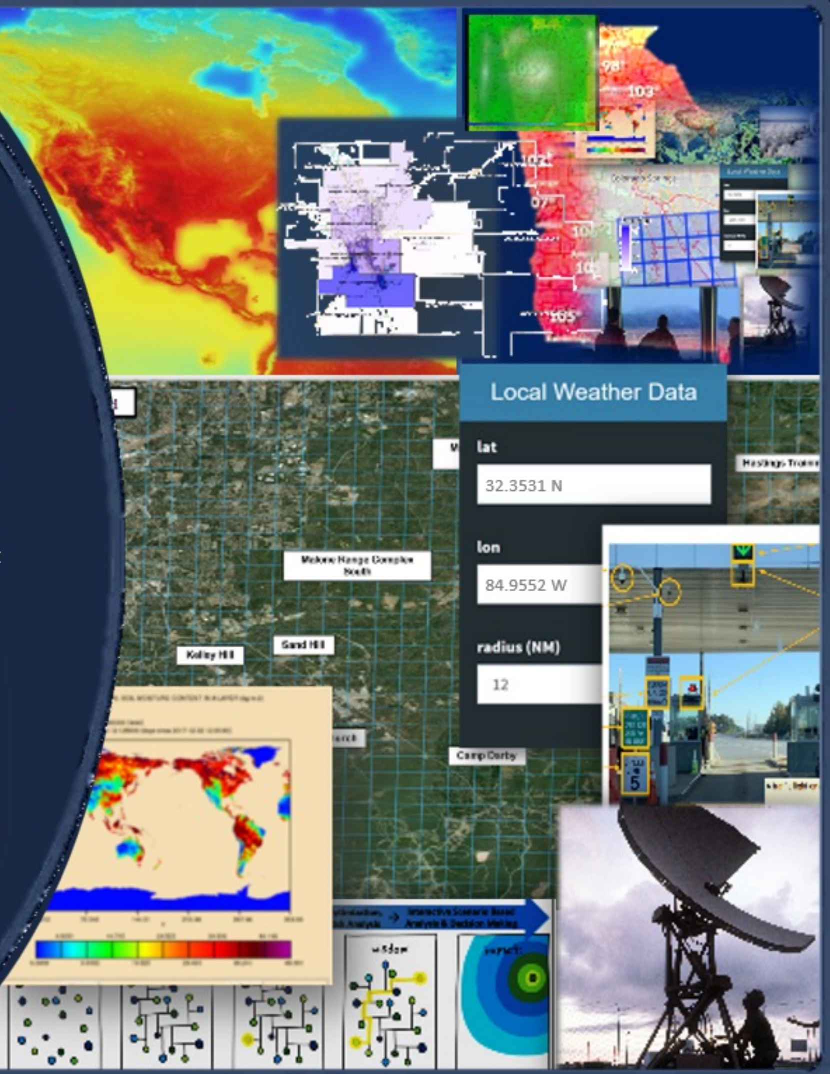
Computer Scientist
Full Stack Development
ERDC ITL

William Anderson
Industrial Engineer
Model Development
ERDC ITL

Charles Sailors
Computer Engineer
Prog/Networks
ERDC ITL



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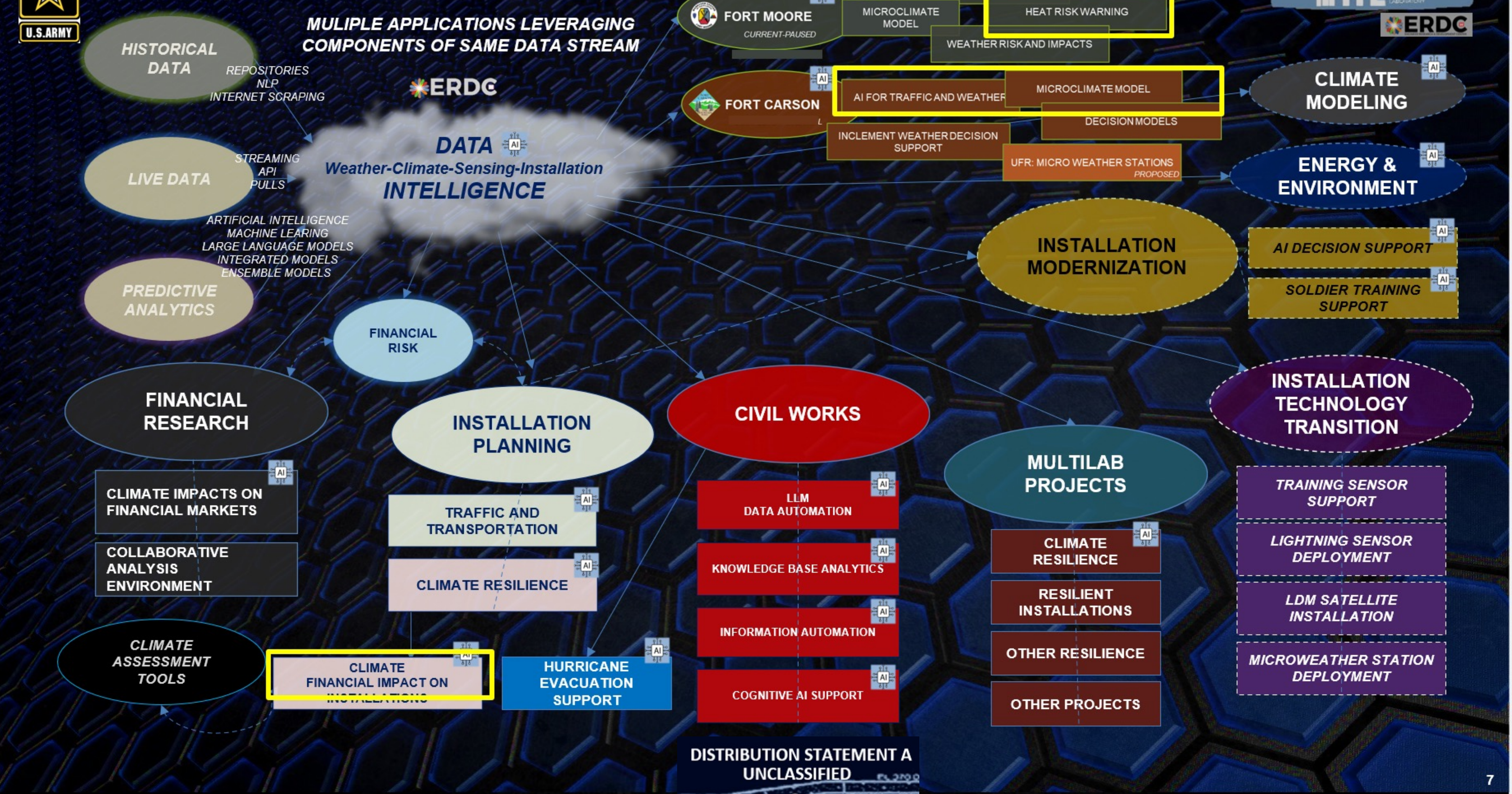
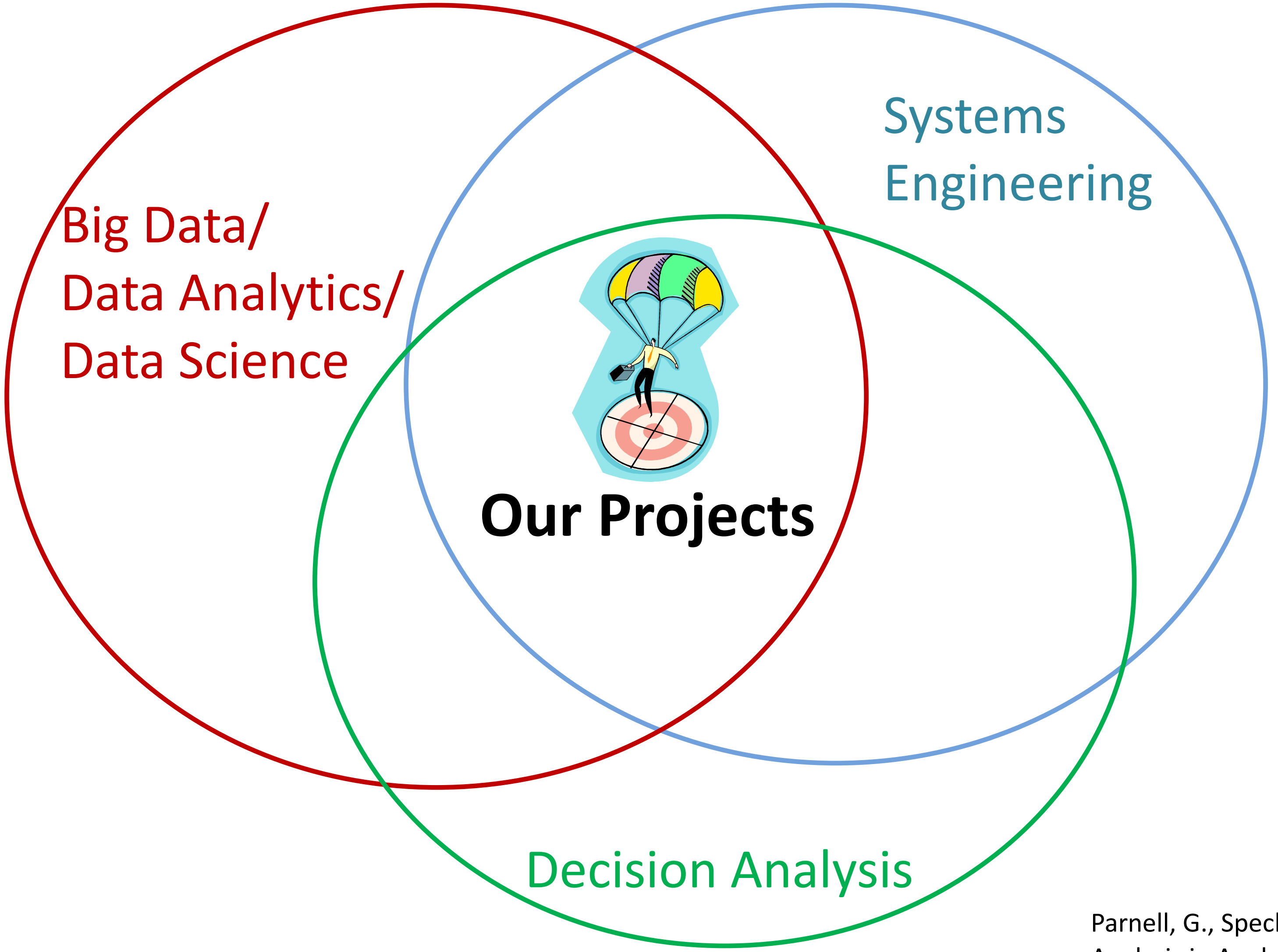
WEATHER CLIMATE DATA INTELLLIGENCE



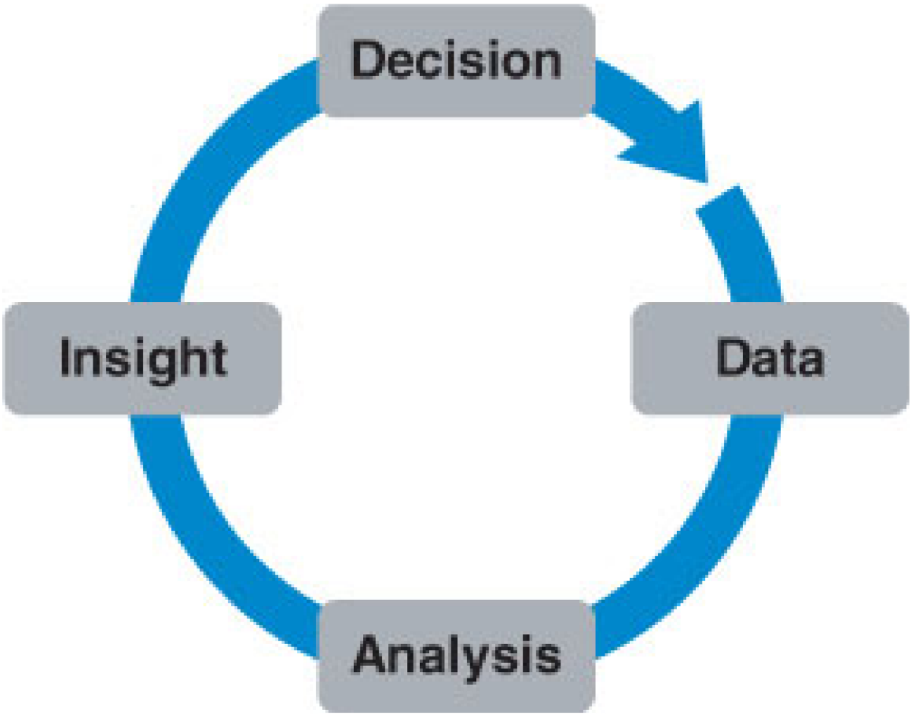
Research Scope



Our DoD and Army Installation projects seek to design systems to support data-driven decision-making.

Parnell, G., Specking, E., Buchanan, R., "Decision Analytics: Using Decision Analysis in Analytics Projects," INCOSE IS, Dublin, Ireland, 2-6 July 2024

INFORMS Analytics Body of Knowledge



Philip T. Keenan, Jonathan H. Owen, Kathryn Schumacher (2022) Chapter 1: Introduction to Analytics. INFORMS Analytics Body of Knowledge:1-30.

We seek to combine the best practices of both perspectives.

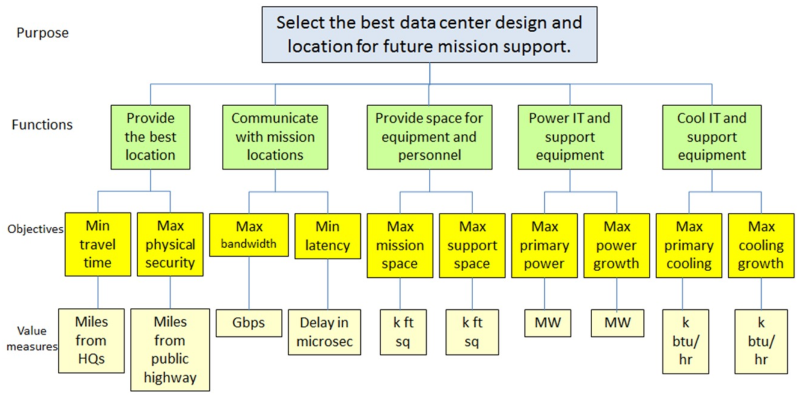
Parnell, G., Specking, E., Buchanan, R., "Decision Analytics: Using Decision Analysis in Analytics Projects," INCOSE IS, Dublin, Ireland, 2-6 July 2024

Table 1.1 Comparison of data-centric and decision-centric approaches.

	Data-centric analysis (Data science, computer science)	Decision-centric analysis (Decision science, operations research)
Mantra	"Start with the data"	"Start with the decision"
Philosophy	Leverage large amounts of data. Let the data "speak freely" by identifying patterns and revealing implicit (hidden) factor relationships	Leverage domain knowledge and subject matter expertise to model explicit variable relationships
Data	More is better, especially for "big data" applications (e.g., speech or image recognition)	Custom collection of curated data sets
Computing	High-performance computing is often price of entry. Potential need for specialized processors (e.g., GPUs, TPUs) for acceptable execution speeds, especially in contexts requiring real-time analysis	Desktop or server-based computing is typical. Trade-offs between potential benefits of leveraging high-performance computing versus added overhead in development and maintenance
Pros	• Increasingly automatable • Potential to extract weak signals from large, unstructured data sets	• Causal focus • Strategic value beyond historical observations
Cons	• Risk of conflating correlation with causation • Analysis inferences are limited by history • Noisy data with confounded effects	• Human subject matter expertise required • Cost of data acquisition can be high
Key disciplines	• Computer science • Data science • Machine learning and unstructured data mining • Artificial intelligence (AI), deep learning	• Management and decision sciences • Operations research • Mathematics • Classical statistics
Example applications	• Image classification • Speech recognition • Autonomous vehicle scene recognition	• Supply chain optimization • Scenario planning • New business model development

Decision Analysis and Data Science Techniques

Multiple Objective Decision Analysis



$$v(x) = \sum_{i=1}^{n} w_i v_i (x_i)$$

$$\sum_{i=1}^{n} w_i = 1$$

Supervised Learning

One Predictor Model

$$Y = \underbrace{\beta_0 + \beta_1 x_1}_{\text{Nonrandom or Systematic Component}} + \underbrace{\varepsilon}_{\text{Random Component}}$$

Multiple Predictor Model

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_q x_q + \varepsilon$$

Where

Y is the outcome value

$x_{1..q}$ is the value of predictor variable

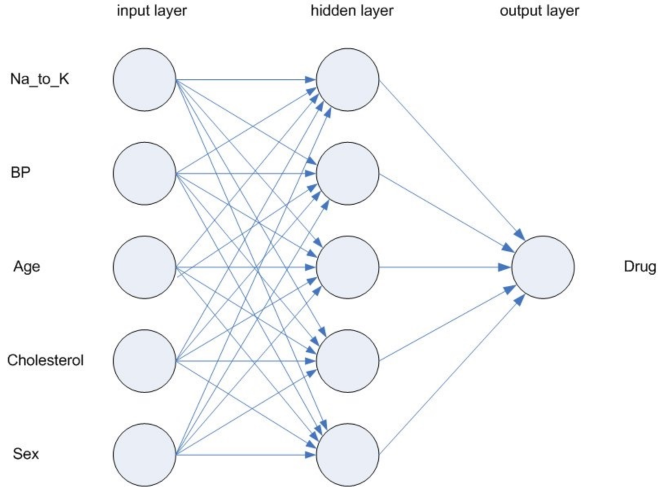
β_0 is the intercept

$\beta_{1..q}$ is the slope coefficient

ε is the error aka residual

https://app.myeducator.com/reader/web/1421a/6/ye1ay/

Neural Networks



https://www.ibm.com/docs/en/spss-modeler/18.0.0?topic=networks-neural-model

The goal of DA and DS techniques are the same. They both have a set of attributes for which the direct relationships are unknown. Many techniques use weights to determine the response variable.

Parnell, G., Specking, E., Buchanan, R., "Decision Analytics: Using Decision Analysis in Analytics Projects," INCOSE IS, Dublin, Ireland, 2-6 July 2024

Data Science Perspective on Five Recent Projects

Project	Descriptive	Predictive	Prescriptive
Unmanned Ground Vehicle Reliability in Conceptual Design	Component technology readiness levels	Predicted performance, reliability, and cost	Feasible alternatives with performance and cost trade-offs
Set-Based Design for Unmanned Aerial Vehicles	Current performance and historical costs	Predicted performance and costs	Feasible alternatives with performance and cost trade-offs
Fort Carson Weather Closure	Historical data on weather and traffic	Weather Nowcast and Forecasts	Grid, Regional, and Installation level warnings
Fort Moore Heat Related Injuries	Historical weather and Heat Related Injuries	Predicting heat related injuries based on weather	Improved unit level training schedule
Climate Change Financial Risk to Installations → All Hazards Risk to Installations	Historical climate, hazard frequency and installation consequences	Extreme weather due to climate and all hazards	Return on investment for installation strategies to be more resilient to all hazards

Parnell, G., Specking, E., Buchanan, R., "Decision Analytics: Using Decision Analysis in Analytics Projects," INCOSE IS, Dublin, Ireland, 2-6 July 2024

INCOSE SE Principles

#	Systems Engineering Principles
1	Systems engineering in application is specific to stakeholder needs, solution space, resulting system solution(s), and context throughout the system life cycle.
2	Systems engineering has a holistic system view that includes the system elements and the interactions amongst themselves, the enabling systems, and the system environment.
3	Systems engineering influences and is influenced by internal and external resource, political, economic, social, technological, environmental, and legal factors.
5	The real system is the perfect representation of the system.
6	A focus of systems engineering is a progressively deeper understanding of the interactions, sensitivities, and behaviours of the system, stakeholder needs, and its operational environment.
7	Systems engineering addresses changing stakeholder needs over the system life cycle.
8	Systems engineering addresses stakeholder needs, taking into consideration budget, schedule, and technical needs, along with other expectations and constraints.
9	Systems engineering decisions are made under uncertainty accounting for risk.
10	Decision quality depends on knowledge of the system, enabling system(s), and interoperating system(s) present in the decision-making process.
11	Systems engineering spans the entire system life cycle.
12	Complex systems are engineered by complex organizations.
13	Systems engineering integrates engineering and scientific disciplines in an effective manner.

Agile Development

Decision & Risk Analysis

Systems Engineering Principles, INCOSE, 2022, https://www.incose.org/publications/products/se-principles, accessed 2 Jun 24

12 of the 15 SE principles are directly relevant to our research.

Parnell, G., Specking, E., Buchanan, R., "Decision Analytics: Using Decision Analysis in Analytics Projects," INCOSE IS, Dublin, Ireland, 2-6 July 2024

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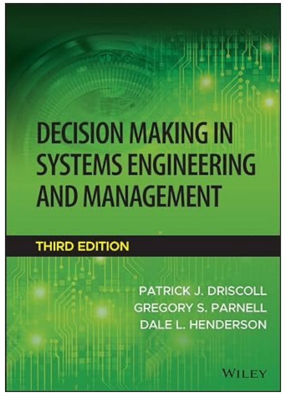
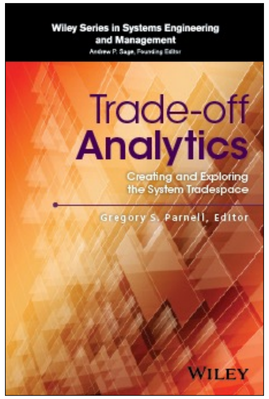
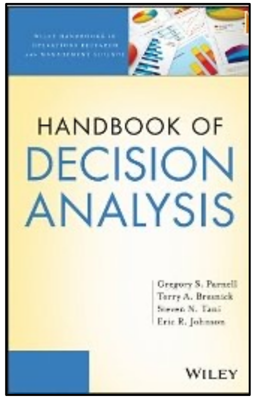
Our research uses decision analysis and systems engineering best practices



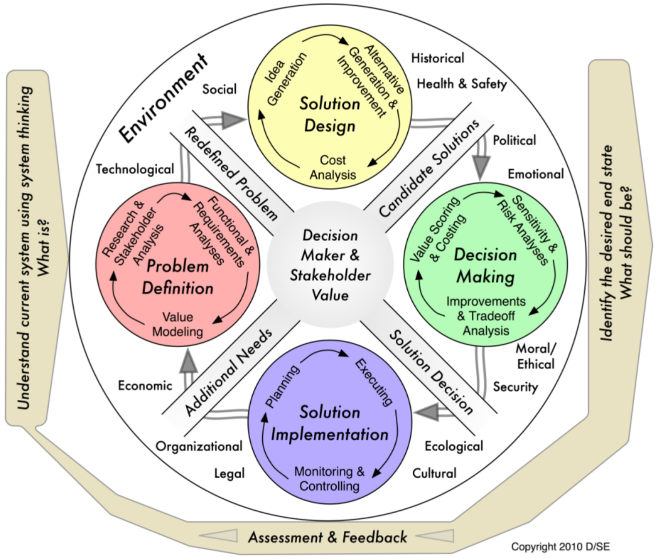
Driscoll, P. H, Parnell, G. S., and Henderson D. L., Editors, **Decision Making for Systems Engineering and Management**, 3rd Edition, Wiley Series in Systems Engineering, Wiley & Sons Inc., 2022



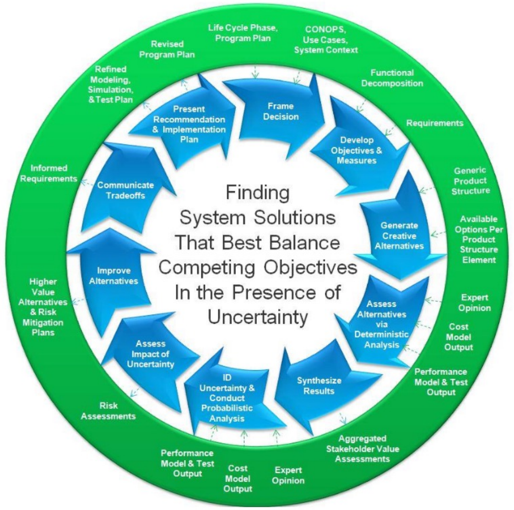
Parnell, G. S., Editor, **Trade-off Analytics: Creating and Evaluating the Tradespace**, Wiley Series in Systems Engineering and Management, Wiley & Sons, Inc.,2017



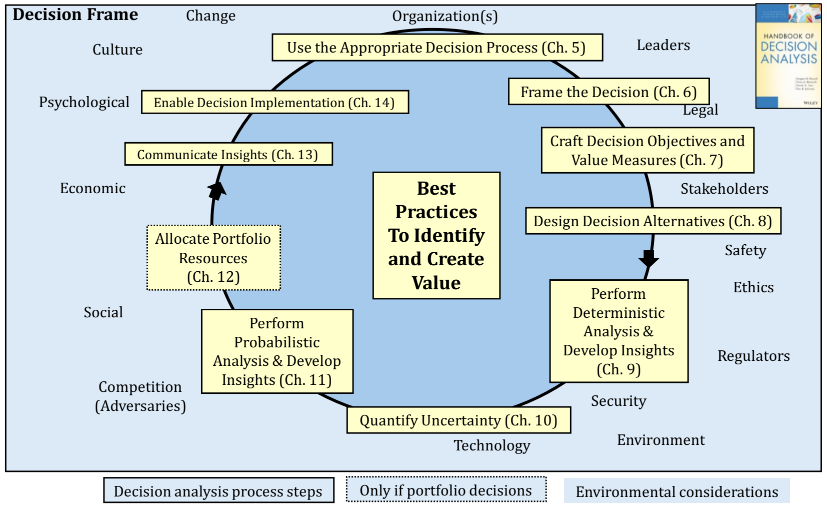
Parnell, G. S., Bresnick, T. A., Tani, S. N., and Johnson, E. R., **Handbook of Decision Analysis** , Operations Research/Management Science Handbook Series, Wiley & Sons, Inc. 2012



Systems Decision Process



Decision Management Process INCOSE Systems Engineering Body of Knowledge



Decision Analysis Process

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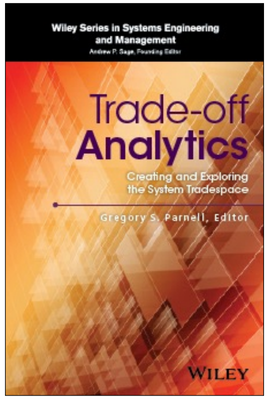
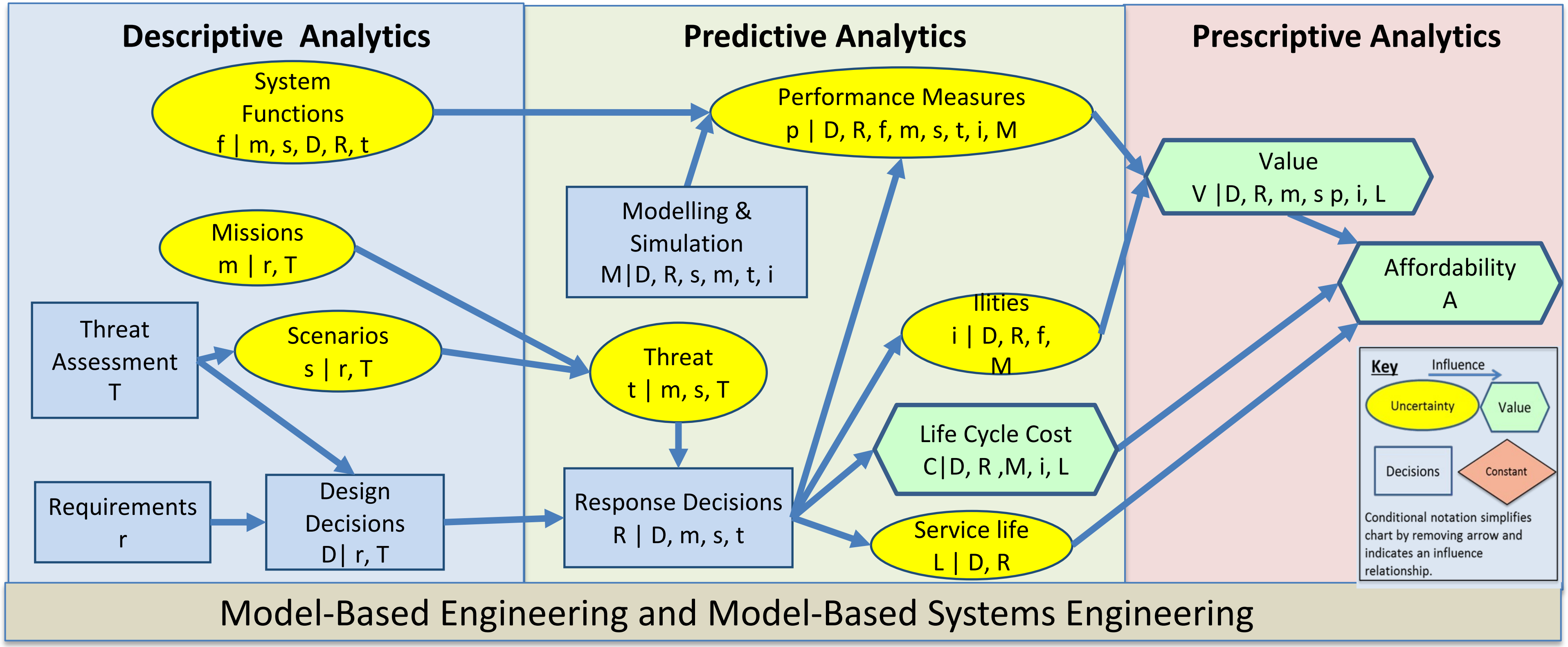
Integrated Trade-off Analytics Framework



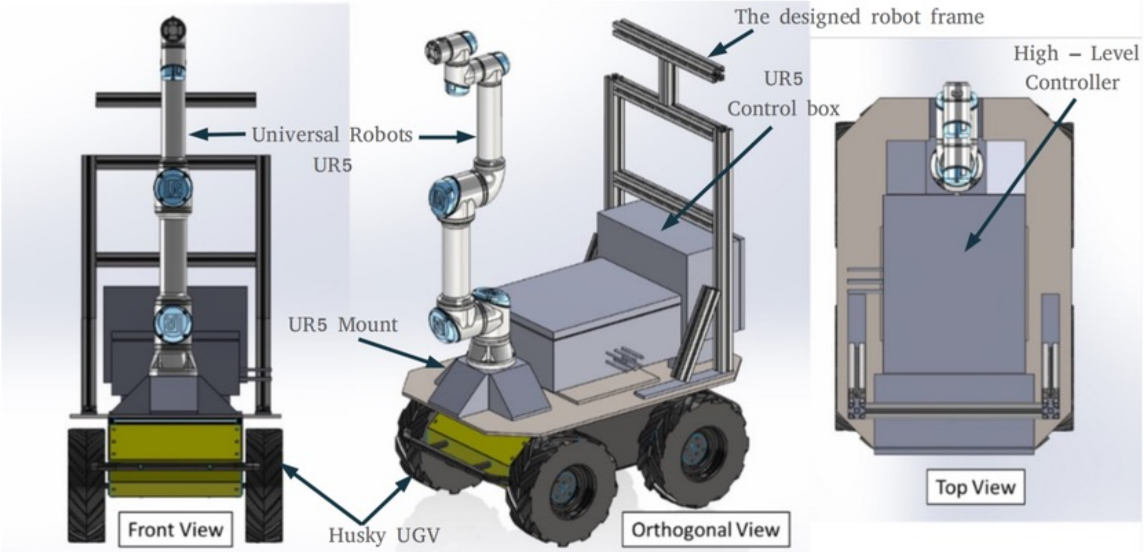
Parnell, G. S., Editor, **Trade-off Analytics: Creating and Evaluating the Tradespace**, Wiley Series in Systems Engineering and Management, Wiley & Sons, Inc.,2017



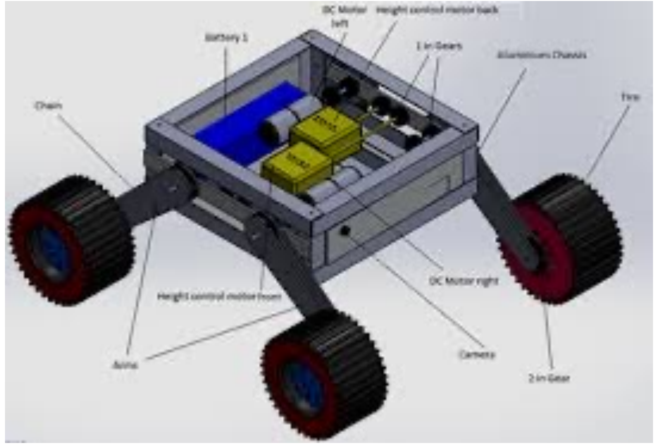
Wade, Z., Parnell, G., Goerger, S., Pohl, E., Specking, E. “Designing Engineered Resilient Systems Using Set-Based Design” 16th Annual Conference on Systems Engineering Research, Charlottesville, Virginia, May 8-9, 2018

Unmanned Ground Vehicles

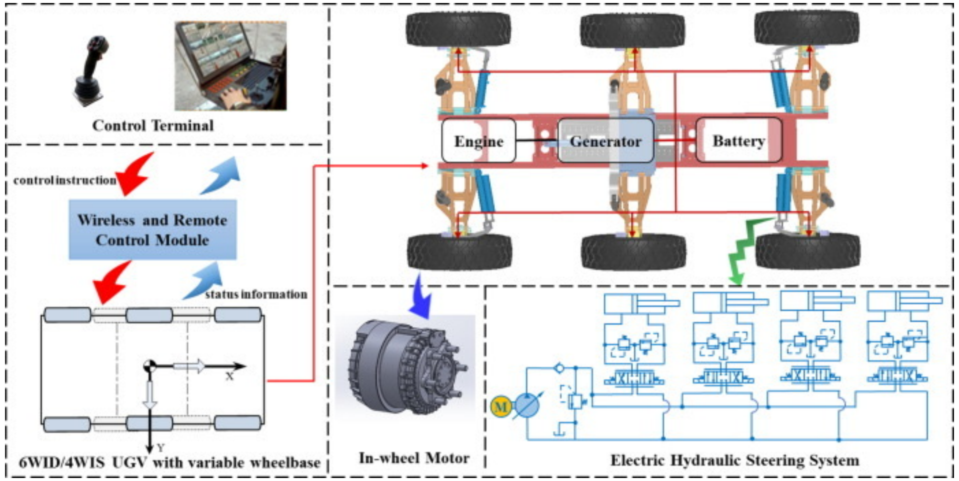
https://www.erdc.usace.army.mil/Media/News-Stories/Article/3595714/unmanned-ground-vehicles-successfully-demonstrated-at-pntax-23/



https://www.researchgate.net/figure/The-design-concept-of-the-reconfigurable-unmanned-ground-vehicle-UGV_fig2_363689679



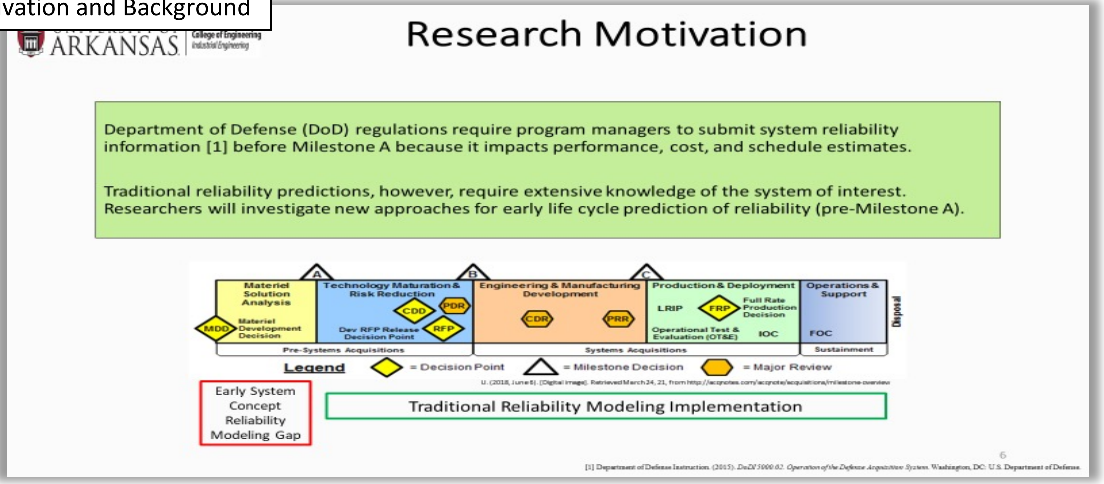
https://hal.science/hal-03375529/document



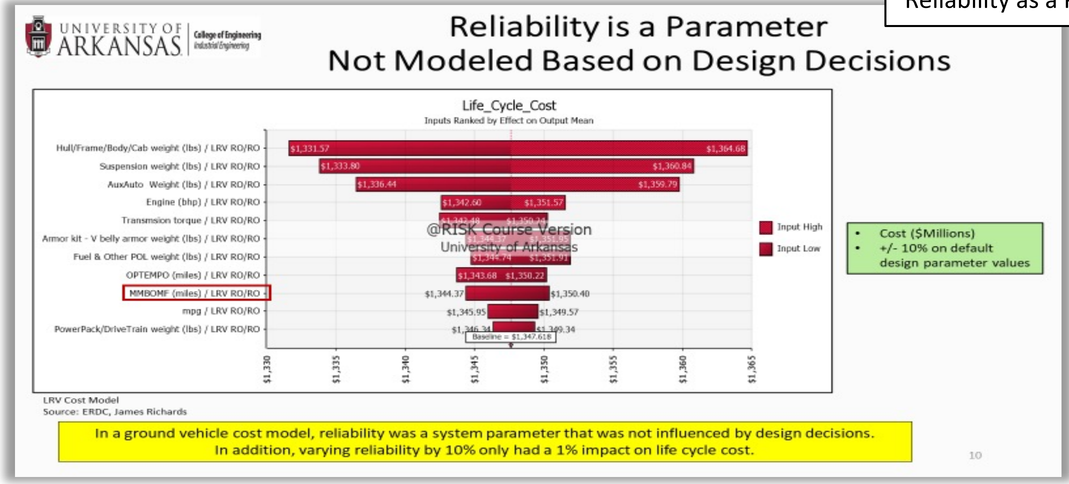
https://www.sciencedirect.com/science/article/abs/pii/S0888327021001102

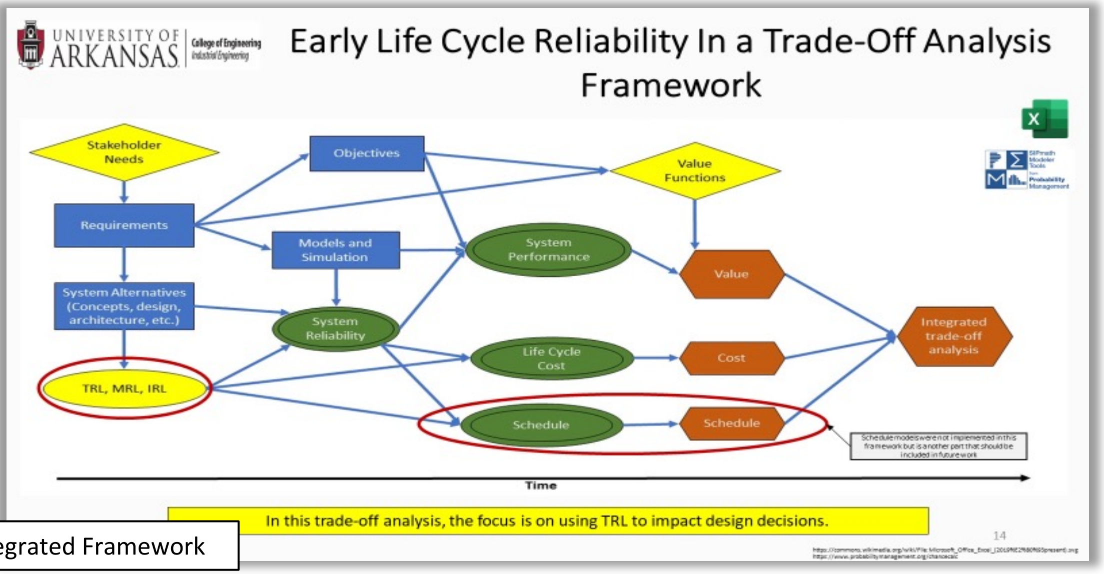
Impact of Reliability in Conceptual Design

Motivation and Background

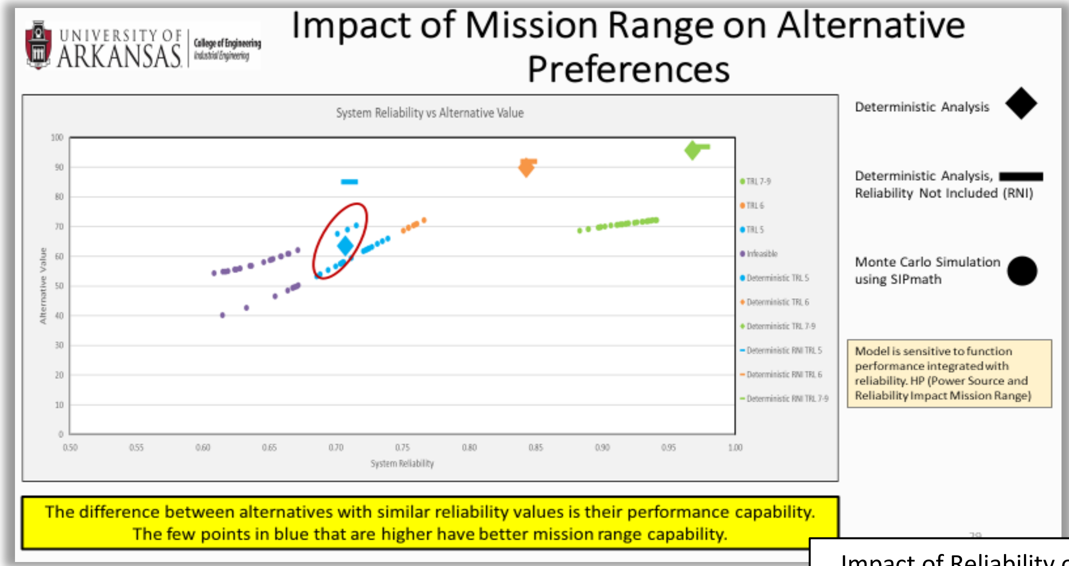


Reliability as a Parameter





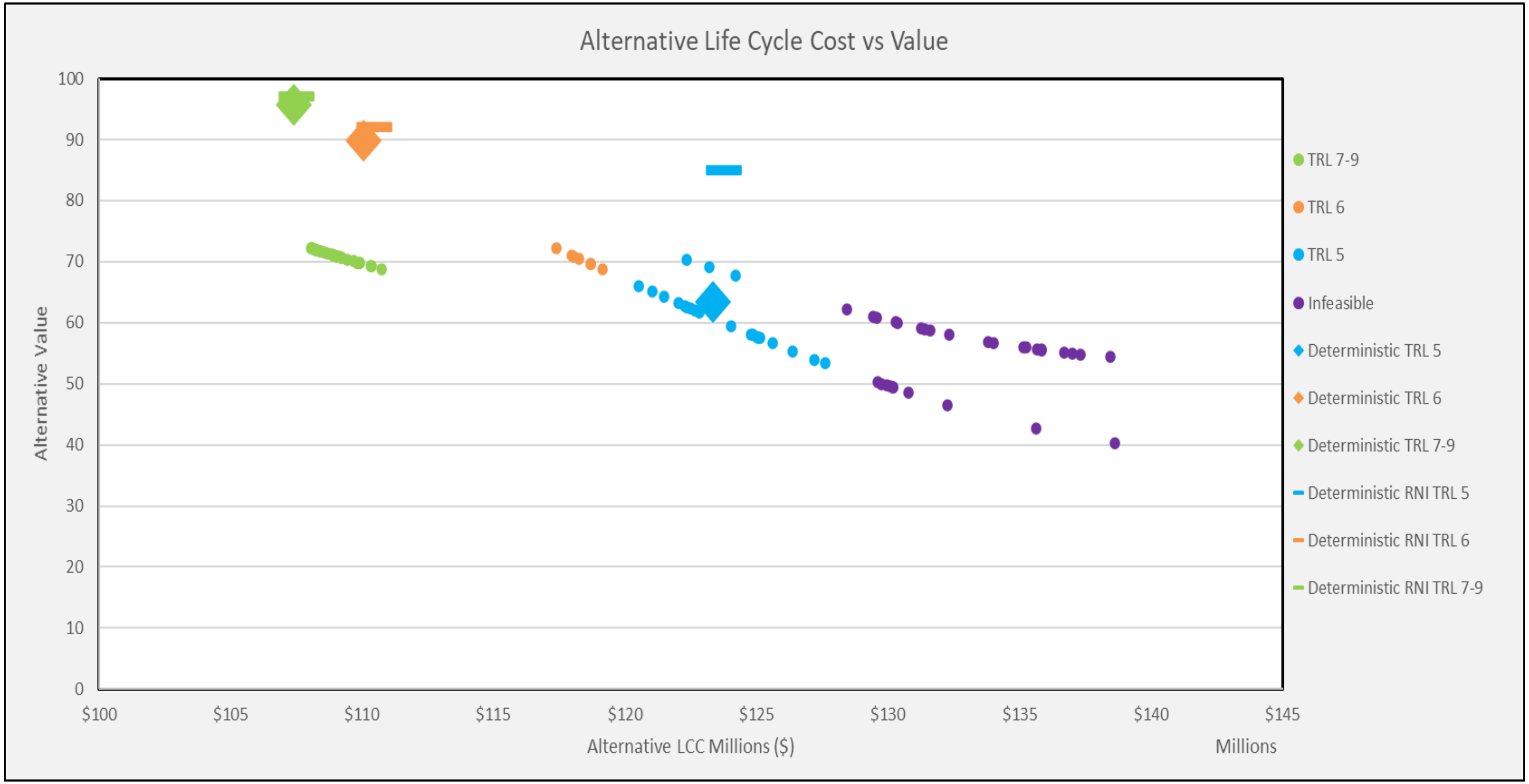
Integrated Framework



Impact of Reliability on Design Space

Barker, T, Parnell, G. S., Pohl, E., Specking, E., Goerger, S. R., and Buchanan, R. K. "Impact of Reliability in Conceptual Design—An Illustrative Trade-Off Analysis", Systems, Special Issue "Model-Based Systems Engineering: From Design to Practical Systems Engineering" Vol 10, Issue 6, November 21, 2022

LCC vs. Alternative Value



Deterministic Analysis

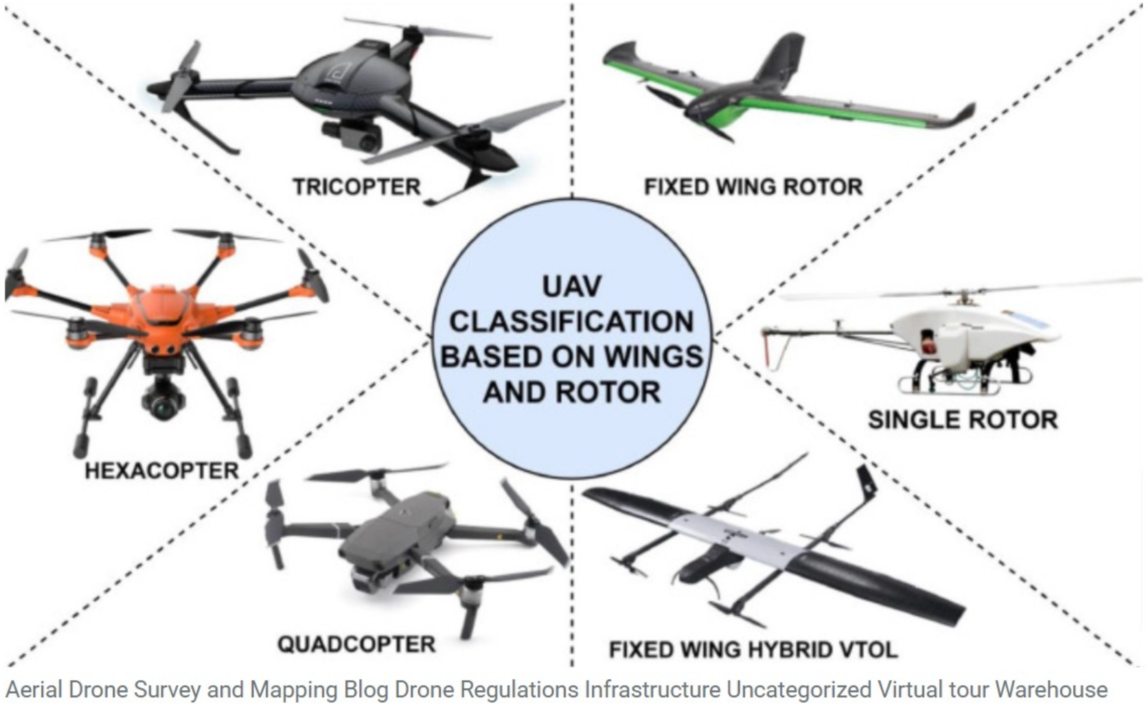
Deterministic Analysis, Reliability Not Included (RNI)

Monte Carlo Simulation using SIPmath

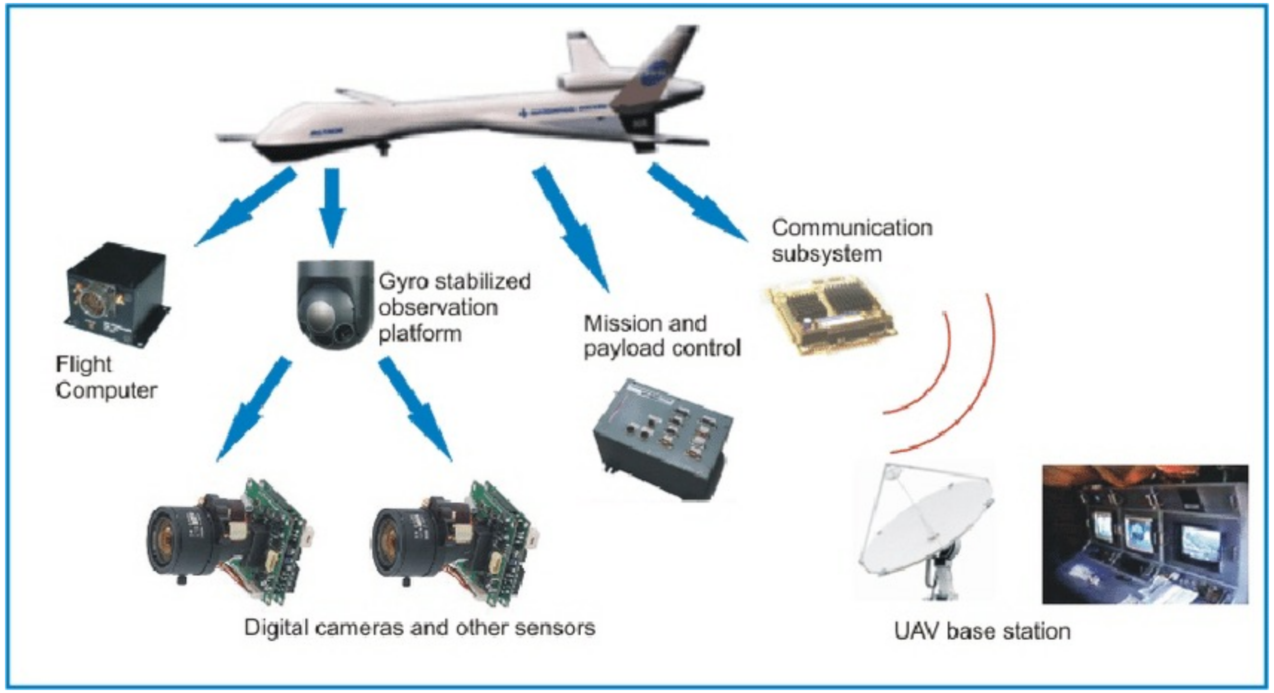
Barker, T, Parnell, G. S., Pohl, E., Specking, E., Goerger, S. R., and Buchanan, R. K. “Impact of Reliability in Conceptual Design—An Illustrative Trade-Off Analysis”, Systems, Vol 10, Issue 6, November 21, 2022

If we do not include reliability in the performance measure mission chains, we may accept costly system designs that may not meet the requirements.

Unmanned Aeronautical Vehicles



https://pigeonis.in/blog/detail-guide-about-uav-technology-supporting-aerial-task-operations/



https://www.researchgate.net/publication/224057242_A_HardwareSoftware_Architecture_for_UAV_Payload_and_Mission_Control/figures?lo=1

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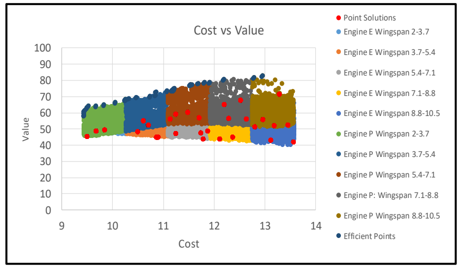
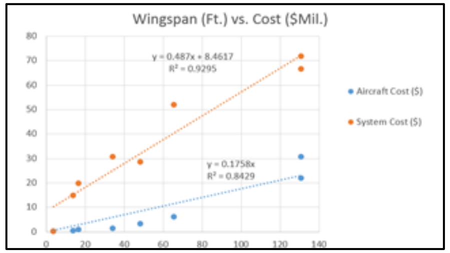
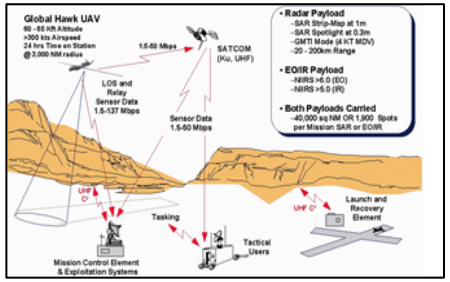
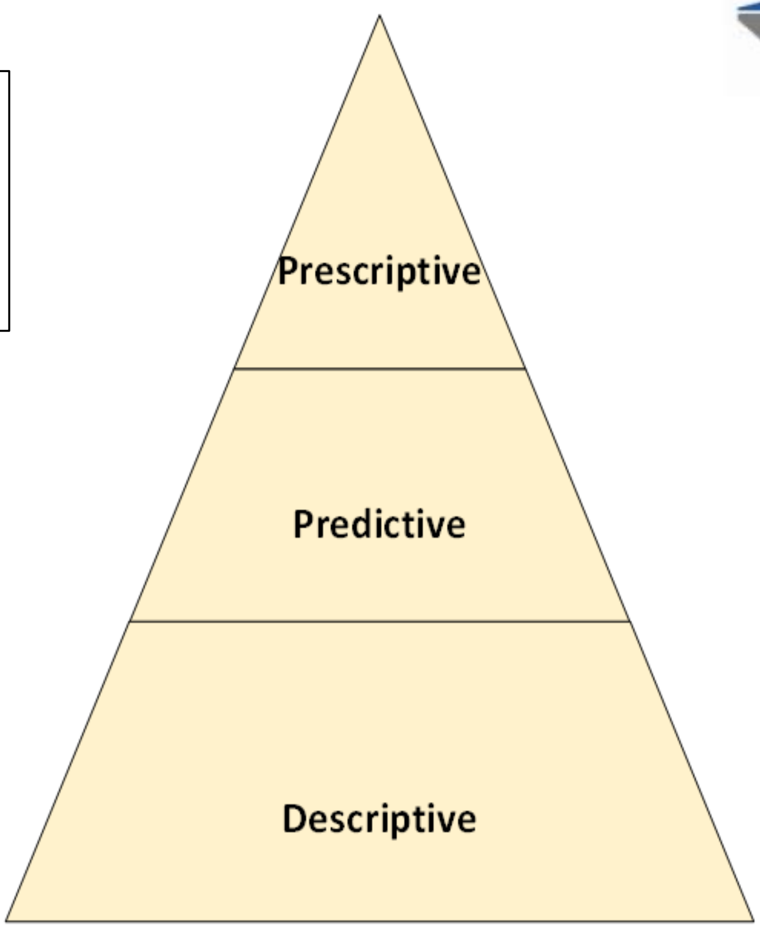
Trade-off Analytics Hierarchy using Set-Based Design with Low Resolution Models









Integrated Value and Cost Model Multiple Objective Decision Analysis

24,949	Feasible Cost vs Value points
5,051	Total infeasible designs
4,825	Infeasible designs with stocastic parameters
226	Infeasible designs with deterministic parameters

Predicted performace and cost models

30,000	Cost estimates
210,000	Value measure estimates
28,741	Design points with stochastic parameters
1,259	Design points with deterministic parameters

Design definition and design parameter calculation

1,260,000	Physics model calculations
5	Value measures with uncertainty
7	Value Measures
30,000	Alternatives generated by SIPmath
10,500	Combinations of design parameters using bins
5	Design Parameters

Specking, E., Parnell, G., Pohl, E., and Buchanan, R., "Early Design Space Exploration with Model-Based System Engineering and Set-Based Design," *Systems*, 2018, Vol 6, No 4.
Small, C. Demonstrating Set-Based Design Techniques—A UAV Case Study. Master's Thesis, University of Arkansas, Fayetteville, AR, USA, 2018.

Integrated Tradeoff Analytics with Set-Based Design and High-Resolution Models

Uncertainty Reduction Focus by Iteration

Design Iteration	Primary Design Uncertainty Source	Secondary Uncertainty Source	Uncertainty Reduction Focus	Primary Design Maturation Focus
1	-	-	Design space exploration	Conceptual system development
2	Payload capacity	Sensor performance	UAV performance	Fuselage & sensor design
3	Sensor performance	Survivability	Sensor performance & detection	Sensor design & operating altitude
4	Payload capacity	Survivability	UAV Performance & detection	Fuselage & sensor design
5	Sensor performance	-	Sensor performance	Sensor design & system resiliency

Uncertainty Reduction Decisions

Design Iteration	Module 1	Module 2	Module 3	Module 4	No. of Unique Design Sets	% Sets Producing Feasible Designs	Generation Time per 100 Thousand points (hrs)
1	1.0	2.0	3.0	4.0	408,240	1.4%	1.1
2	1.0	2.1	3.0	4.0	26,250	18%	1.9
3	1.2	2.1	3.2	4.2	12,000	37%	5.1
4	1.3	2.3	3.3	4.2	729	89%	10.2
5	1.3	2.3	3.3	4.3	16	100%	18.5
Total computation time (all iterations): 81.4 hours							

Design Maturation Decisions

Design Iteration	Number of Available Design Options During Iteration							No. Unique Design Sets
	Engine Type	EO Sensor Res.	EO Sensor FOV	IR Sensor Res.	IR Sensor FOV	Wingspan (No. Bins)	Altitude (No. Bins)	
1	2	9	6	9	6	10	7	408,240
2	1 [a]	5	5	5	5	6	7	26,250
3	1	4	5	4	5	5	6	12,000
4	1	3	3	3	3	3	3	729
5	1	2	2	2	2	1 [a]	1 [a]	16

[a] Design option locked into final system configuration

1. **Using integrated performance, cost, and schedule analytics is a "best practice" for digital engineering and model-based engineering of complex systems to enable tradespace exploration.**
2. **Pareto optimality, based on LR designs and models, in early design does not guarantee feasibility or achievement of system requirements.**
3. **SBD prevents premature design decisions (either selection or elimination) helping to mitigate program risk.**
4. **Using integrated models for complex systems, quantitative SBD can inform design maturation decisions and reduce uncertainty.**
5. **Quantitative SBD deliberately preserves design options until uncertainty is reduced; provides program flexibility to achieve performance, cost, and schedule objectives.**

Shallcross, N.J., Parnell, G.S., Pohl E., Goerger S., "Using Value of Information Methodology in Quantitative Set-Based Design." *Systems Engineering*. 2021; Vol 24, Issue 6, 2021, pp. 439-455

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Ft Carson Weather Warning

https://www.facebook.com/USArmyFortCarson/photos/a.421021314733/10159528103419734/?type=3

https://medium.com/my-public-affairs/how-fabulous-is-fort-carson-884e87f48d0a

https://www.solarpowerworldonline.com/2020/12/can-your-solar-project-weather-a-hailstorm/

https://www.facebook.com/USArmyFortCarson/posts/colorado-winter-is-on-its-way-along-with-unpredictable-weather-often-bringing-sn/493936719433017/

https://www.cnn.com/2020/10/12/us/colorado-wildfire-fort-carson-army-base-trnd/index.html

Fort Carson Weather Warning Decision Hierarchy

Tran, M.; Kreinberg, S.; Specking, E.; Parnell, G.S.; Hernandez, B.; Pohl, E.; Gallarno, G.; Richards, J.; Buchanan, R.; Rinaudo, C. Smart Installation Weather Warning Decision Support. Systems, 2024, 12, 14.

Already Made

- Locations of Weather Stations
- Data Sources (Observations, Forecasts, Traffic)
  - NWS Provides Forecast Data
- WWA List & Fort Carson Forecast Checklist
- Grid and Region Locations
- ERDC VTIME
- Other Weather Data Sources as needed

Our Decisions

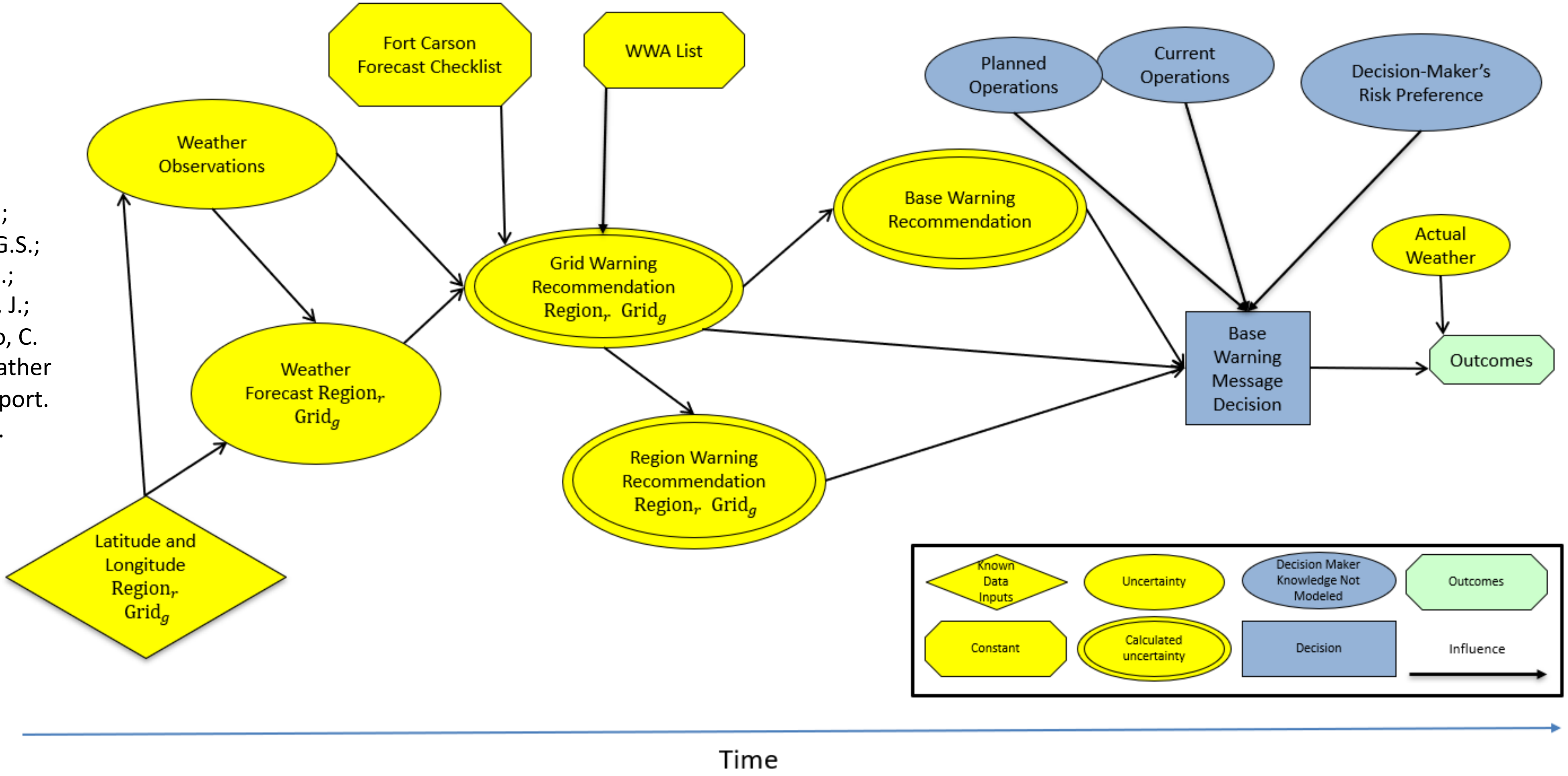
- Assess Grid Level Warning
- Assess Region Level Warning
- Calculate Installation Level Warning
- Incorporate traffic risk
- Develop Minimum Viable Product
- Add capabilities

Subsequential Decisions

- US Ignite Develops and Deploys Visualization Dashboard
- Operational Decisions
- Installation Decisions

Fort Carson Weather Warning Decision Influence Diagram

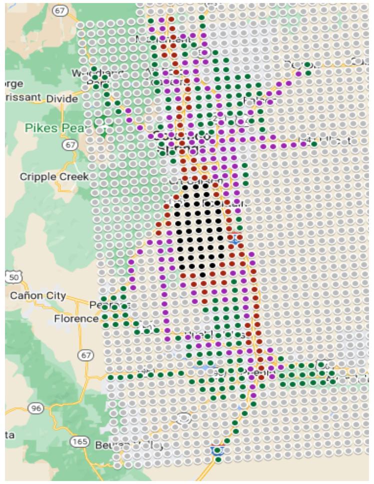
Tran, M.; Kreinberg, S.; Specking, E.; Parnell, G.S.; Hernandez, B.; Pohl, E.; Gallarno, G.; Richards, J.; Buchanan, R.; Rinaudo, C. Smart Installation Weather Warning Decision Support. Systems, 2024, 12, 14.



During agile development, the influence diagram helped our team, the stakeholders, and decision makers have a common understanding of the courses of our data and how the decision would be made.

Weighting Grids and Triggering Warnings

Score	Description	Color
5 Most Critical	geographical grids on the Fort Carson base	Black
4	geographical grids on major highways or areas near Fort Carson	Red
3	geographical grids on highways that feed major highways or areas close to the Fort Carson base	Purple
2	geographical grids in residential areas or areas on highways that are not that near to the Fort Carson	Green
1 Least Critical	all other geographical grids	White



ArcGIS

Used ArcGIS to validate Python code.

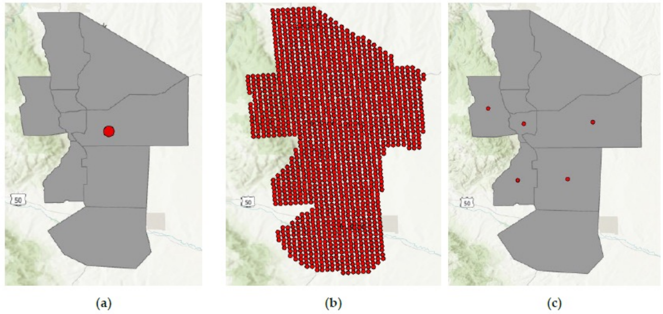
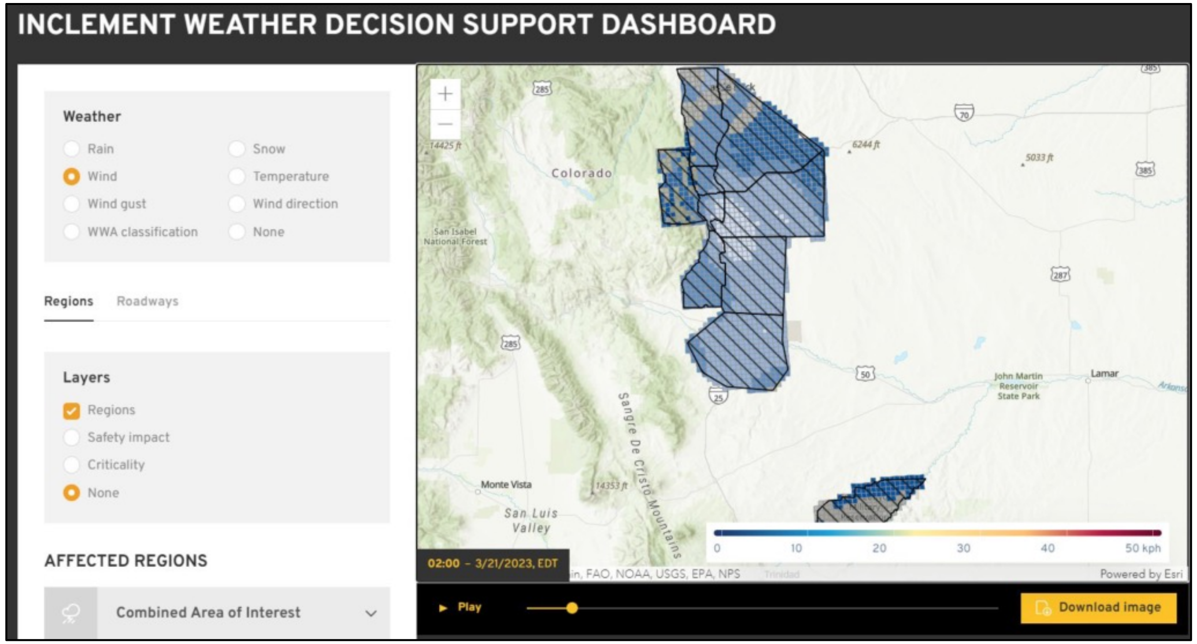


Figure 9. Triggering the grid, region, and installation levels for watch_surfaceWindsO45 condition. (a) Installation level; (b) grid level; (c) region level.



Tran, M.; Kreinberg, S.; Specking, E.; Parnell, G.S.; Hernandez, B.; Pohl, E.; Gallarno, G.; Richards, J.; Buchanan, R.; Rinaudo, C. Smart Installation Weather Warning Decision Support. Systems, 2024, 12, 14.

Fort Moore Heat Injuries

https://www.stripes.com/branches/army/2023-07-31/army-heat-injury-troops-temperatures-weather-10920317.html

https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.moore.army.mil%2Finfantry%2Frtb%2F&psig=AOvVaw1lwUxvcaYumZjxtYmmzaT&ust=1717529565100000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCNDPnq-WwIYDFQAAAAAdAAAAABAW

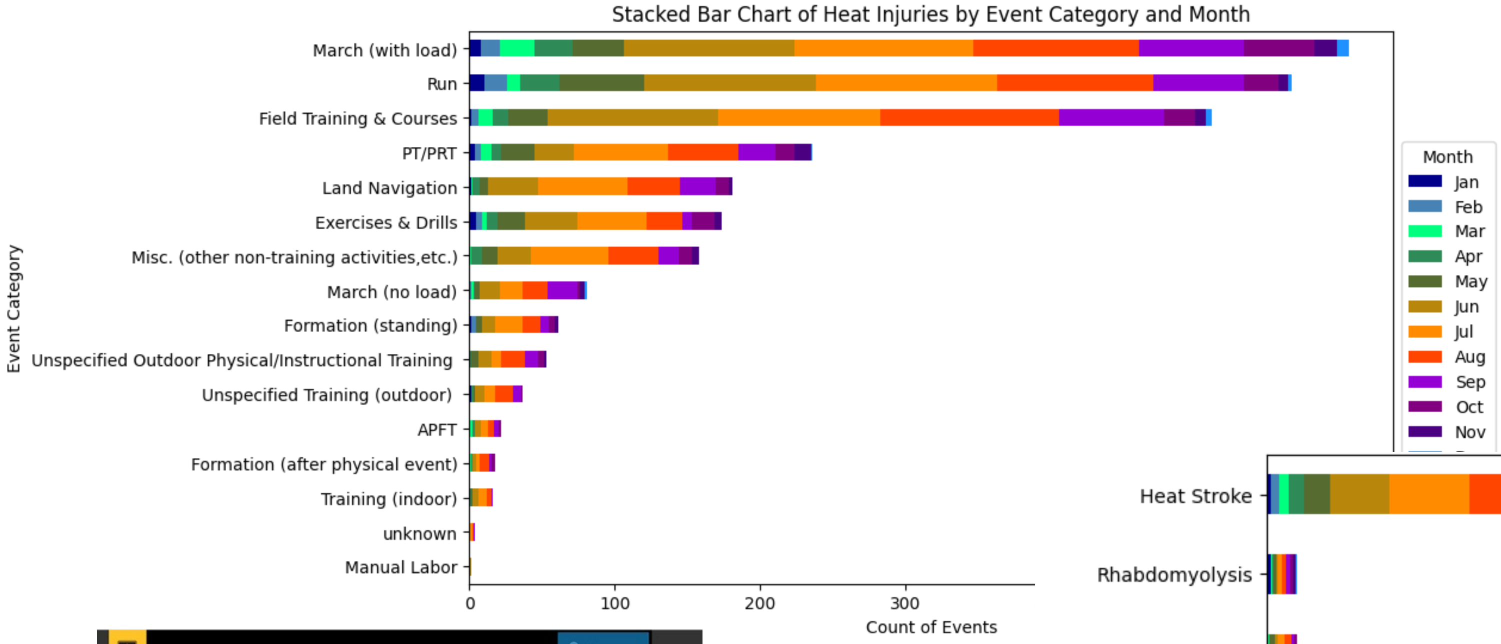
https://courtneystockton.com/fort-benning-ga-infantry-basic-training-graduation-4/

https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.youtube.com%2Fwatch%3Fv%3DIxv6PklywOM&psig=AOvVaw1lwUxvcaYumZjxtYmmzaT&ust=1717529565100000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCNDPnq-WwIYDFQAAAAAdAAAAABAQ

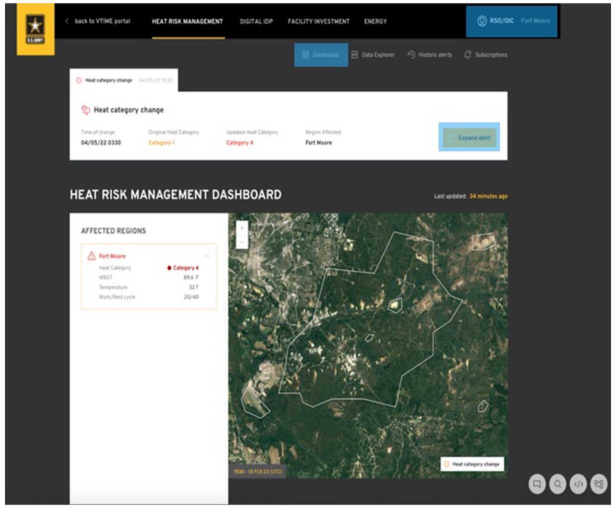
https://www.facebook.com/FortBenningMCoE/photos/us-army-soldiers-from-b-co-1-46-infantry-conduct-a-16k-ruck-march-jan-20-2017-he/10154988896064184/

https://www.rallypoint.com/locations/fort-benning-ga?cid=hi-DeOr

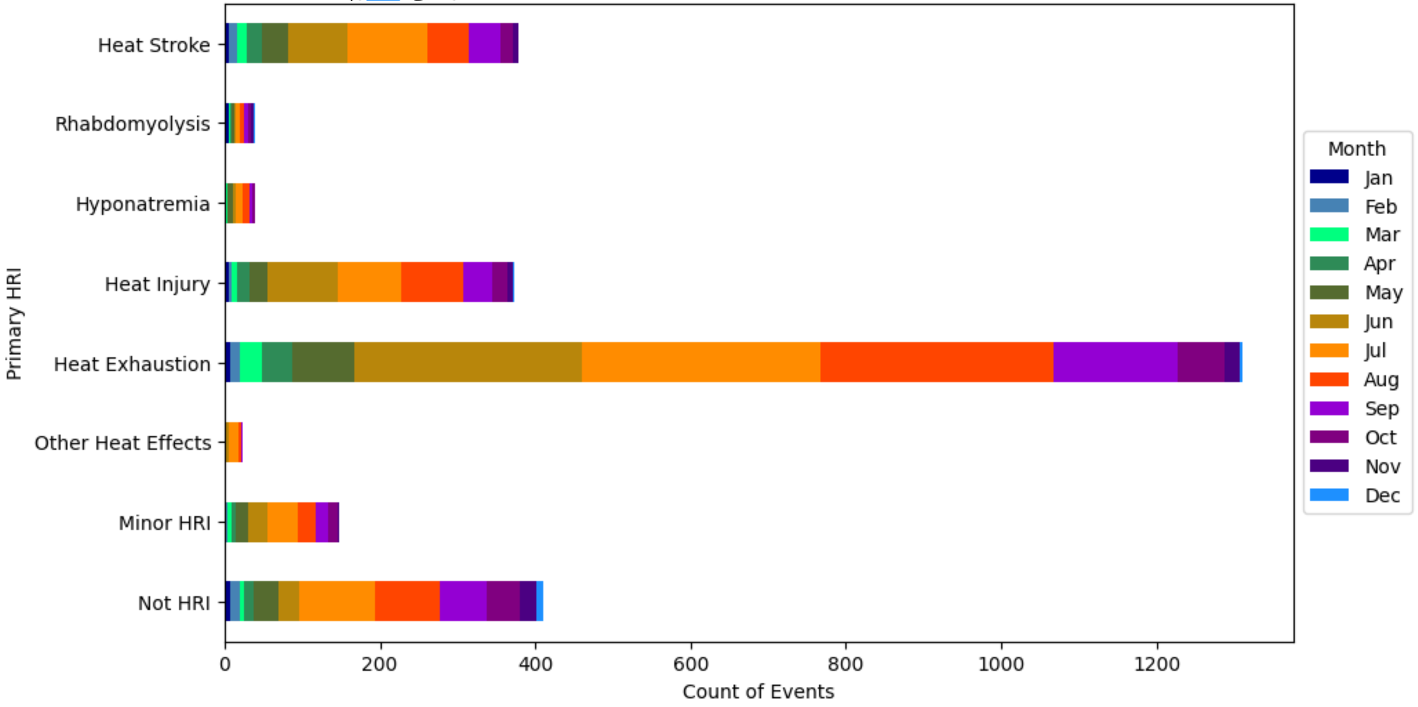
Data Analytics



Franks, W., Beger, A., Specking, E., Parnell, G. S., Pohl, E., Anderson, W., Buchanan, R., and Richards, J., “Improving Training Risk Assessment for Heat Related Injuries at Fort Moore”, *Military Operations Research*, Submitted on 9 Feb 24.

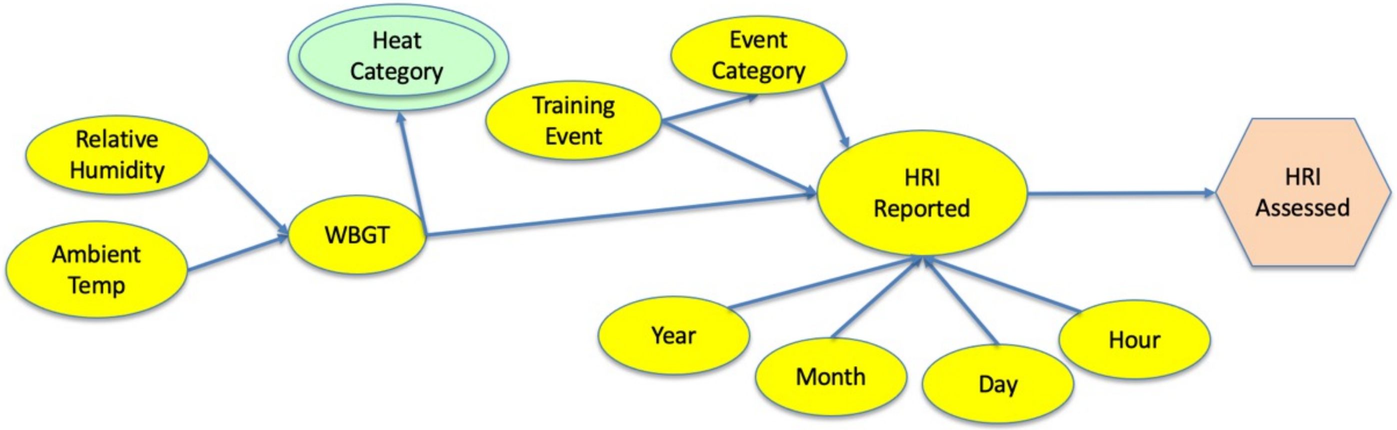


https://www.us-ignite.org/blogs/how-us-ignite-is-helping-fort-moore-mitigate-heat-related-risks/

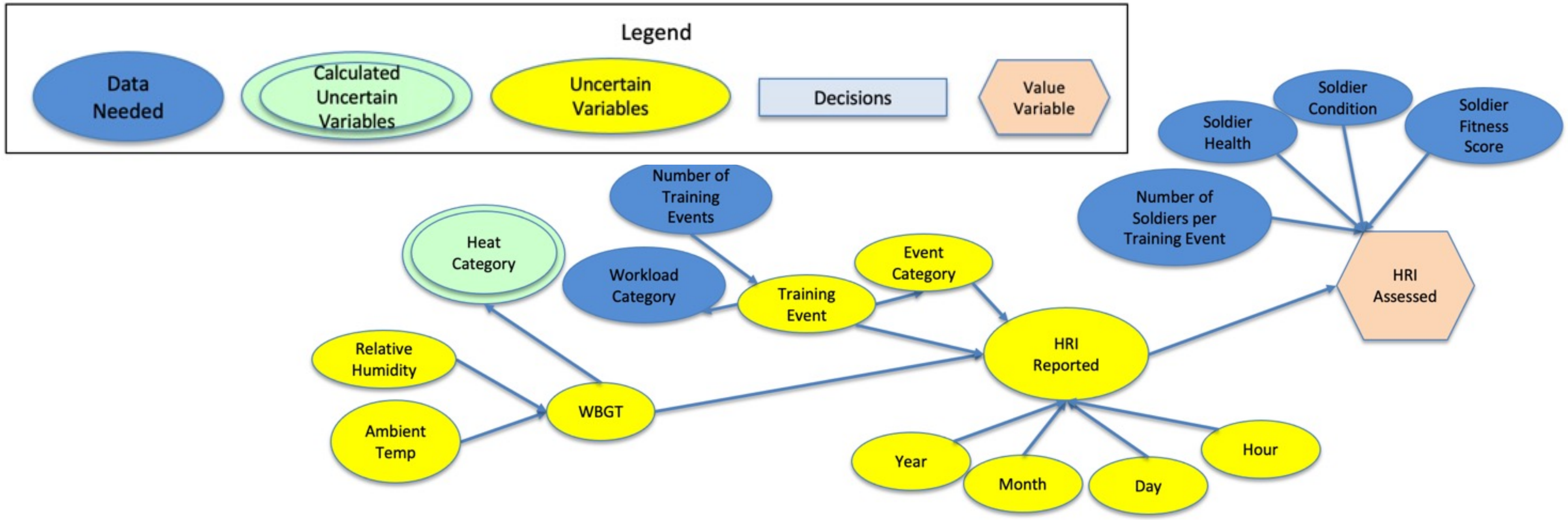


Fort Moore Heat Related Injuries

Franks, W., Beger, A., Specking, E., Parnell, G. S., Pohl, E., Anderson, W., Buchanan, R., and Richards, J., “Improving Training Risk Assessment for Heat Related Injuries at Fort Moore”, *Military Operations Research*, Submitted on 9 Feb 24.



Data provided all events that have been assess in the field as HRIs.



Minimum essential data needed to inform training leaders of the probability of an HRI during a potential training event at a given day and time.

Extreme Weather Damage

https://x.com/WeatherNation/status/1668415385442344964

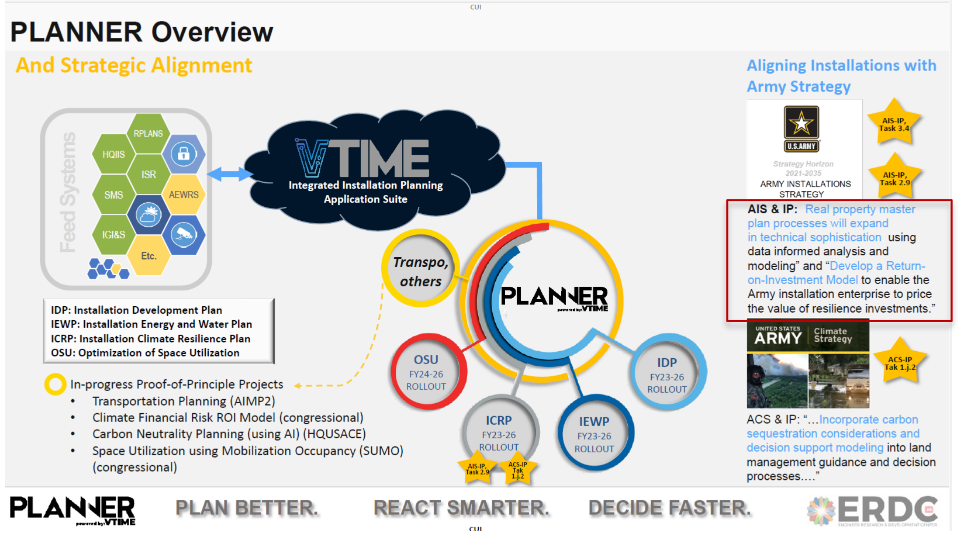
https://www.denverpost.com/2017/01/12/fort-carson-building-wind-damage/

www.weather.gov/safety/flood-states-co

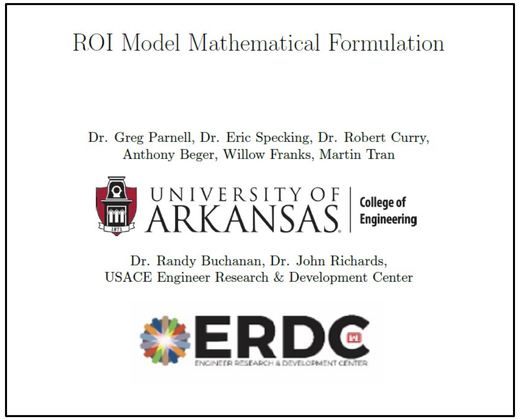
https://gazette.com/news/grass-fire-at-fort-carson-forces-evacuation/article_2d0262cd-eaa6-59a6-ac1f-0a670701bc1f.html

Resilient Option ROI Model

Task



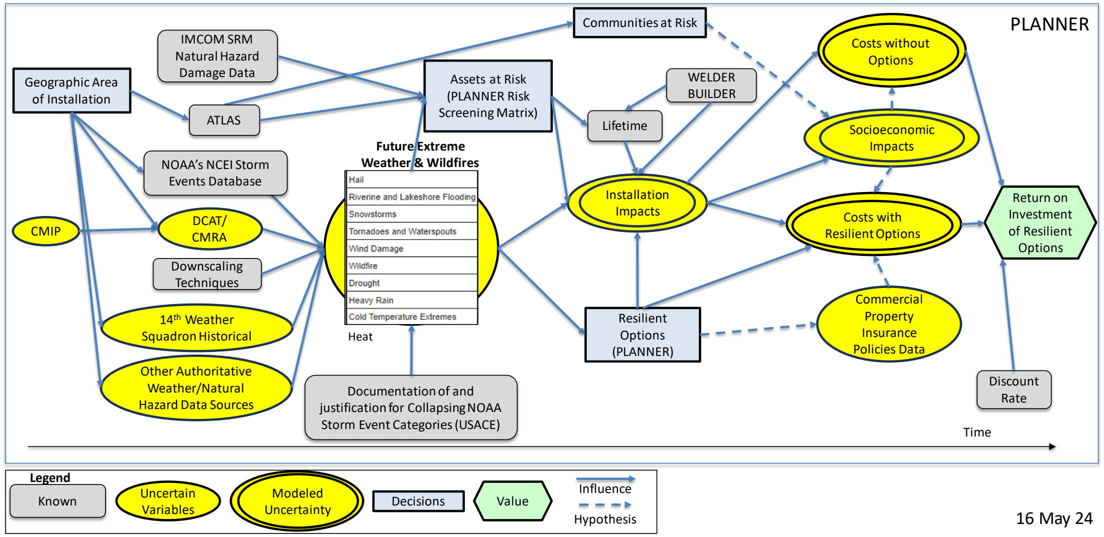
Risk Based ROI Model for Installation Resilient Options



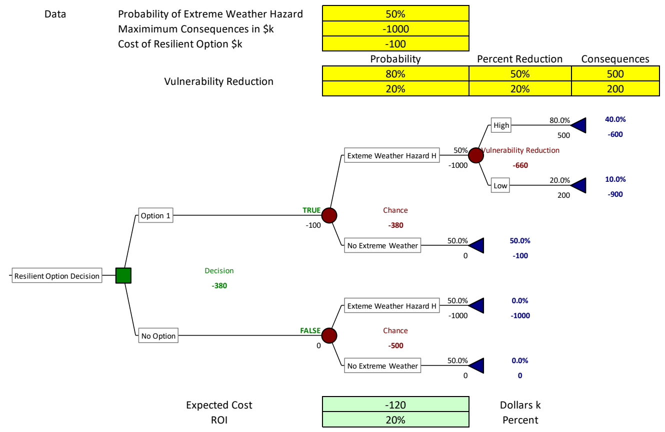
Assumptions

- Model uses hazard likelihood, asset vulnerability, and asset consequence data
- Options can impact 1 or more hazard
- Hazards can impact 1 or more assets
- PLANNER inputs → Model inputs
- Probabilities → Forecast/Historical Distributions

Methodology



Minimum Viable Product ROI Example for one asset and one hazard with PLANNER inputs



Example illustrates a resilient strategy with a 20% ROI.

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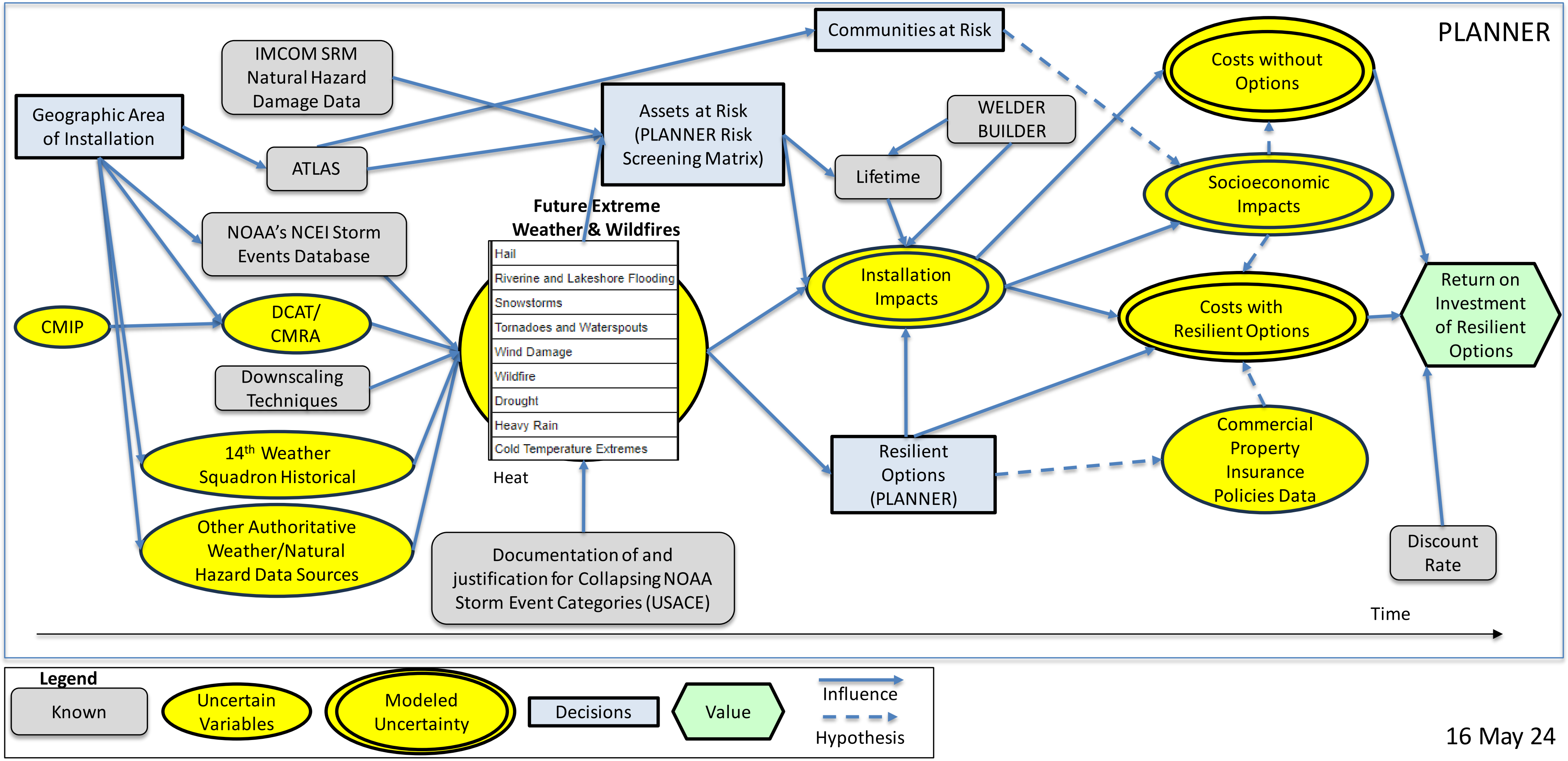
ERDC ENGINEER RESEARCH & DEVELOPMENT CENTER

Influence Diagram for ROI Model for Financial Impact of Climate Change on Army Installations



16 May 24

During agile development, the influence diagram helped our team, the stakeholders, and decision makers have a common understanding of the sources of data and how ROI would be calculated.

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COLLEGE OF ENGINEERING

ROI Model Interviews

ERDC
ENGINEER RESEARCH & DEVELOPMENT CENTER

Jeremey Alcorn
Climate and Sustainability Officer
Director, Climate and Sustainability
27 Feb 24

Major Will Henning, USAF
Lt Col Benjamin Fulk, USAFR
Dr. Jason Patla
3 Apr 24

Wesley Bushnell
MEDCOM PM and MILCON Economist
Branch Chief for Planning and Programming
Engineering and Support Center
26 Mar 24

Weather Effects on the Lifecycle of DoD Equipment Replacement (WELDER) Lawrence Berkeley National Laboratory
Dr. Peter Larsen
8 Apr 24

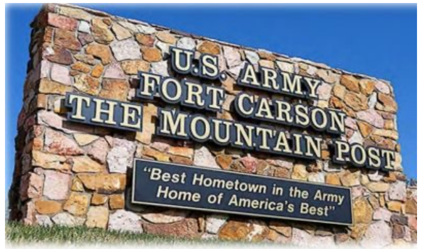
Tim Shugert
Chief, Real Estate Division
New England District
9 Feb 24

Dan Palmer
Chief, Cost Estimating Division
New England District
2 Apr 24

Chris Hatfield
Chief, Plan Formulation Branch
New England District
1 Mar 24

VTIME
James Stinson, Ph.D.
Computer Scientist
ITL
29 Apr 24

FIA
Louis (Buddy) Bartels
FIA Developer
James Stimson
29 Apr 2024



John Sanders (Fort Carson)
Stephen Evans (AMC)
9 May 24

Beth Lachman
R. J. Briggs
10 May 24

Stakeholder interviews have been in important part of our research.

UNCLASSIFIED

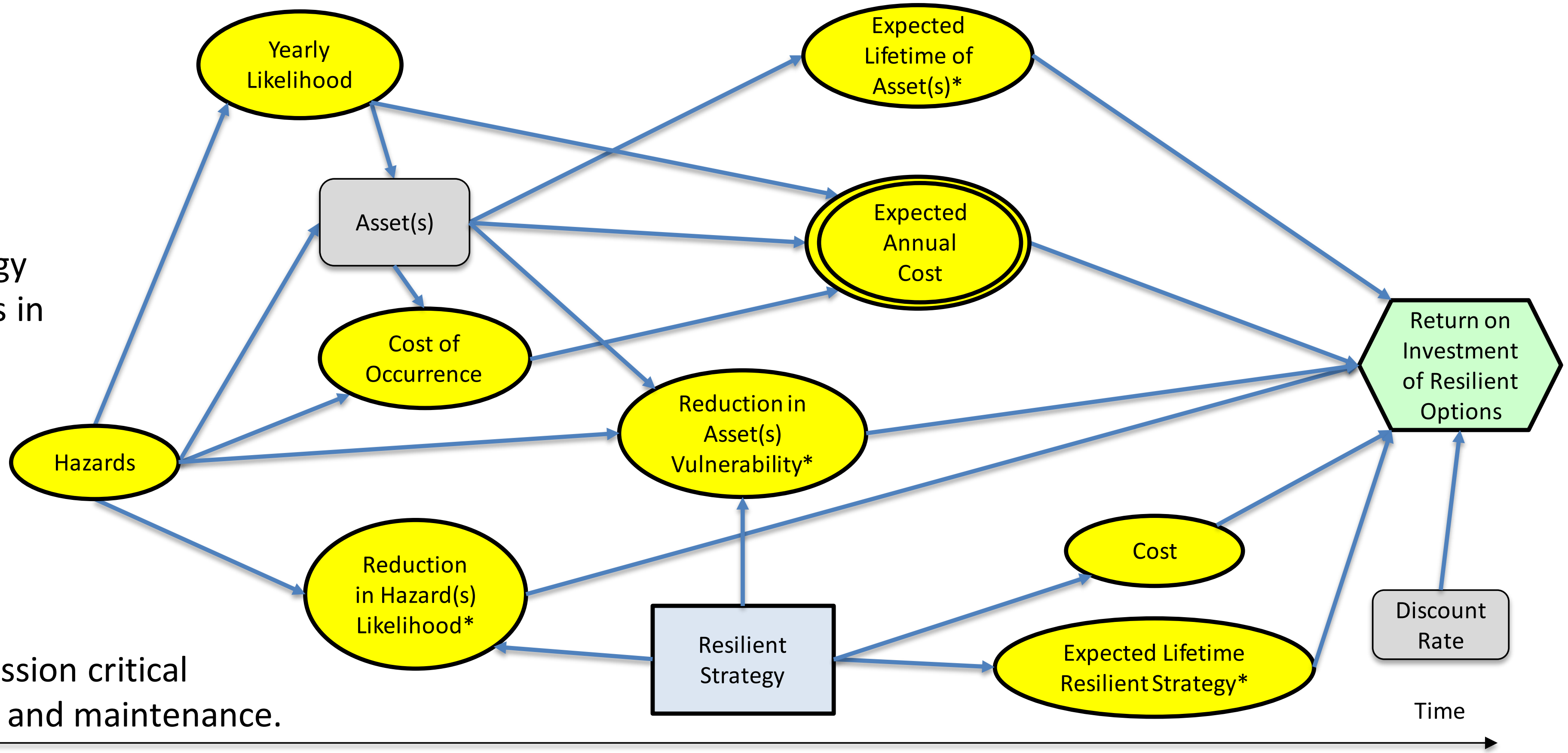
Influence Diagram for ROI Model for Financial Impact of Climate Change on Army Installations

PLANNER

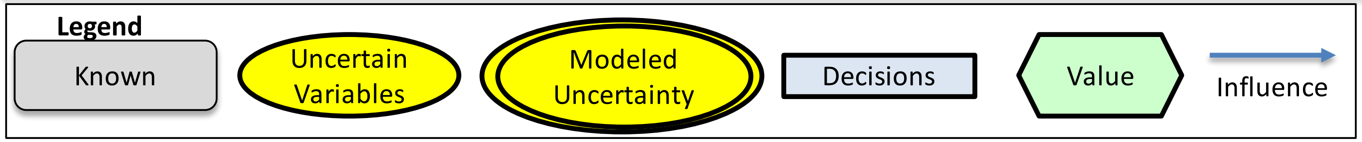
ROI Model
Standard engineering risk terms and methods

MVP Data Sources
PLANNER Risk Matrix
PLANNER Resilient Strategy
*Forge will add data fields in PLANNER

Goals
All Hazards
Model Driven Data



ROI is not required for mission critical construction, operations, and maintenance.



ROI model would be used to assess investments in older assets.

17 Jun 24

Formulated the ROI Model Goal

ROI Model Mathematical Formulation

Dr. Greg Parnell, Dr. Eric Specking, Dr. Robert Curry,
Anthony Beger, Willow Franks, Martin Tran

UNIVERSITY OF ARKANSAS | College of Engineering

Dr. Randy Buchanan, Dr. John Richards,
USACE Engineer Research & Development Center

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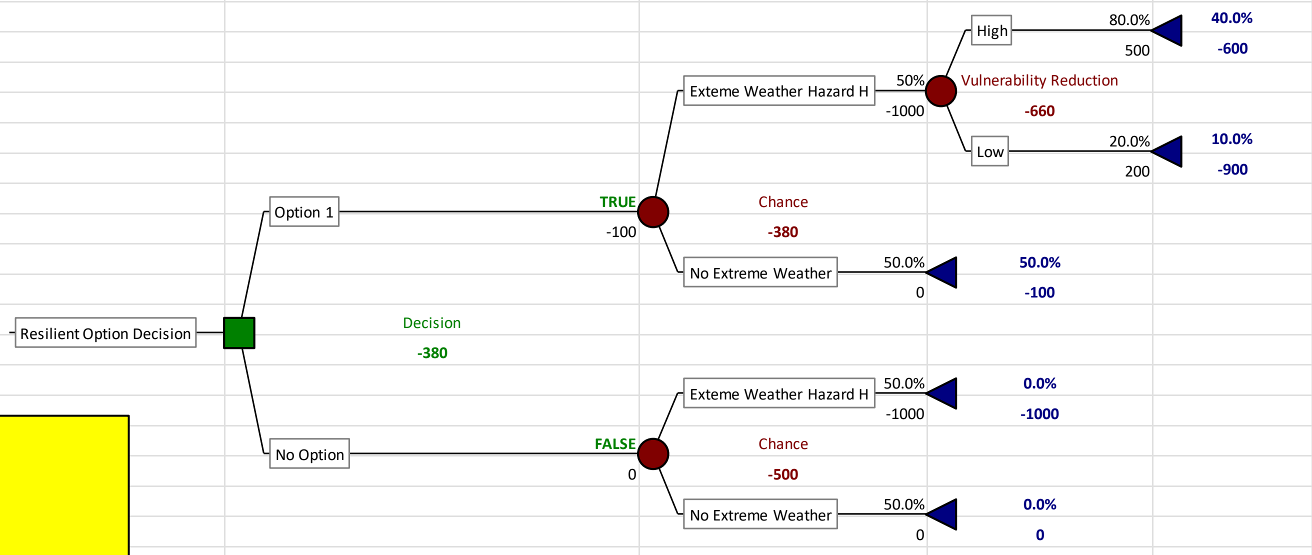
Decision Tree for One Hazard and One Resilient Option

Maximimum Consequences in $k	-1000		
Cost of Resilient Option $k	-100		
	Probability	Percent Reduction	Consequences
Vulnerability Reduction	80%	50%	500
	20%	20%	200



Expected Cost	-120	Dollars k
ROI	20%	Percent

Model Formulation Challenges for Army installations

- Severe weather due to climate change → All Hazards
- Risk is function of likelihood, vulnerability, and consequences
- Consequences assessed in dollars
- A hazard can impact multiple assets
- A resilient option can reduce likelihood and/or consequences
- A resilient option can impact one or more assets

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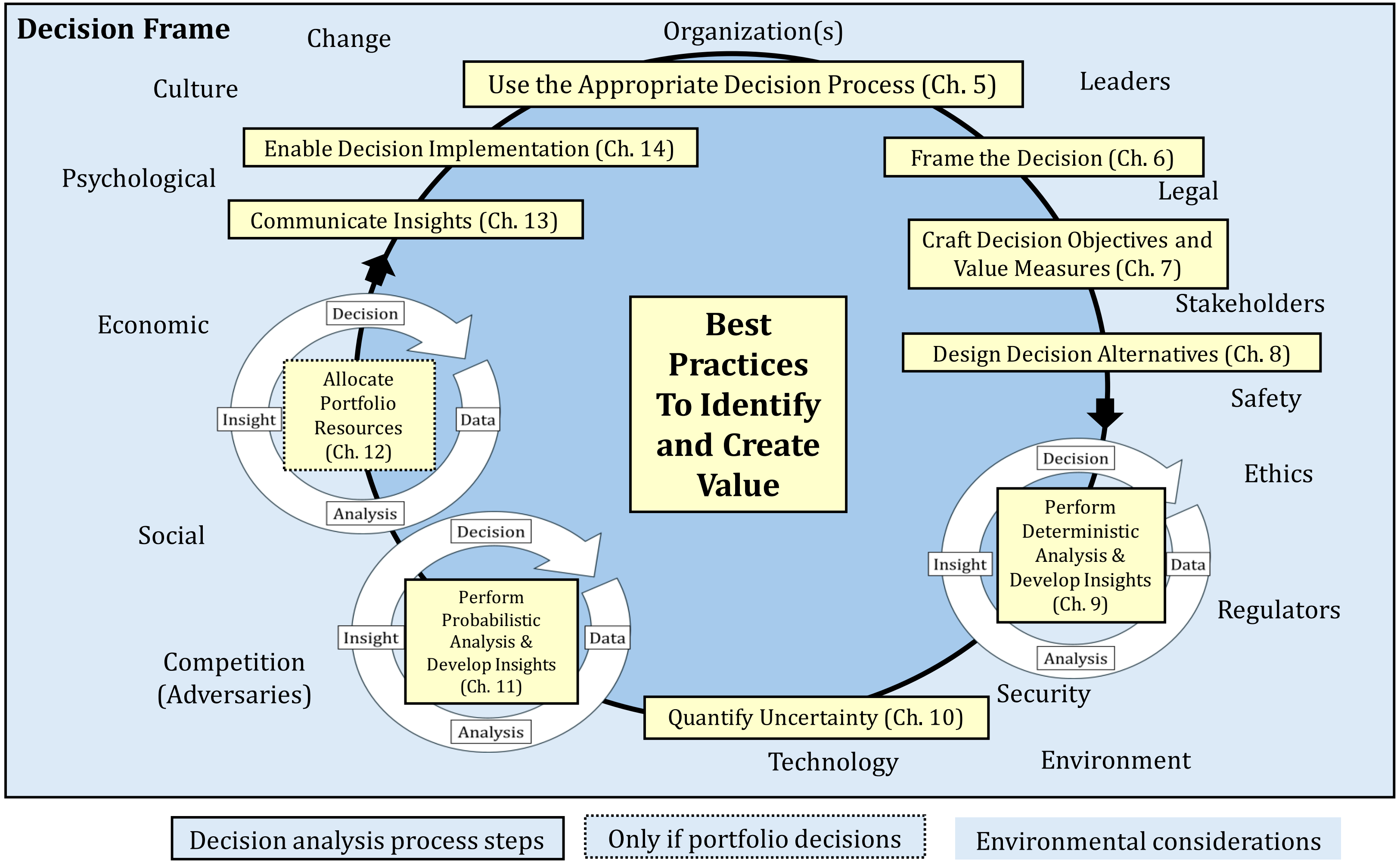
Decision Analysis, 2nd Edition



We do deterministic model before probabilistic model because "arithmetic comes before statistics" Devon Clark, INCOSE colleague, May 2024.

Parnell, G. S., Bresnick, T. A., Tani, S. N., Johnson, E. R., and Specking E. A., **Handbook of Decision Analysis**, Wiley & Sons, Inc. Operations Research/Management Science Handbook Series, **2nd Edition**, 2025

Authors

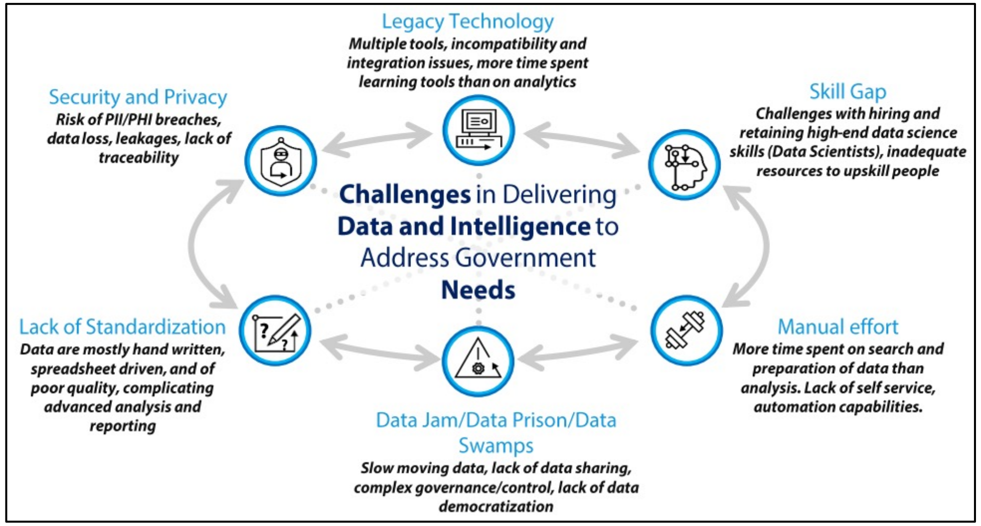
4 Society for Decision Professional Fellows
2 Certified Analytic Professionals
2 Certified System Engineering Professionals

Changes

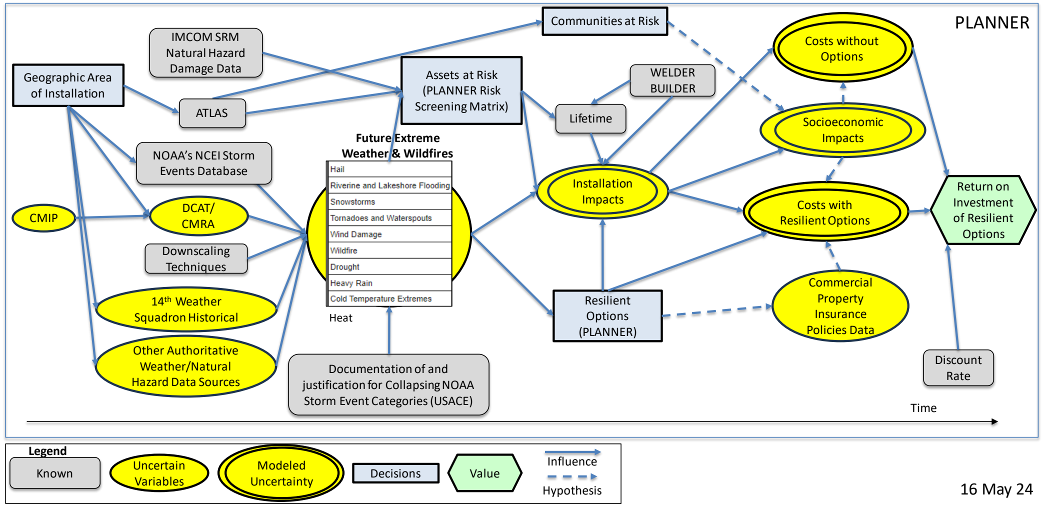
- Decision analysis is a prescriptive model that uses descriptive and predictive analytics
- Influence diagrams integrated into Ch 6 as a major decision framing technique
- Three illustrative examples with step-by-step examples.

Summary

Data Analytics Challenges in Public Sector

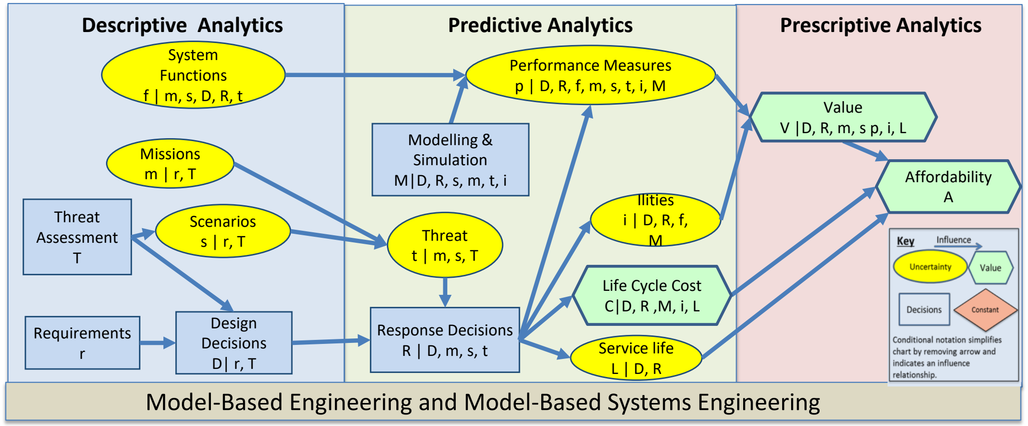


Decision Framing Tools: Influence Diagrams

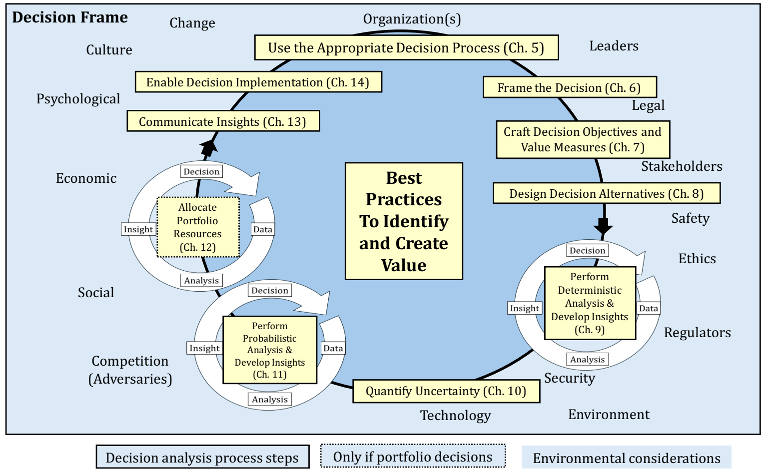


16 May 24

Data Science, Analytics and Decision Analysis



Integrate Data Analytics and Decision Analysis



Parnell, G. S., Bresnick, T. A., Tani, S. N., Johnson, E. R., and Specking E. A., **Handbook of Decision Analysis**, Wiley & Sons, Inc. Operations Research/Management Science Handbook Series, **2nd Edition**, 2025