Modeling the Effect of Sea-Level Rise on Risks to Coastal Infrastructure Using Bayesian Networks

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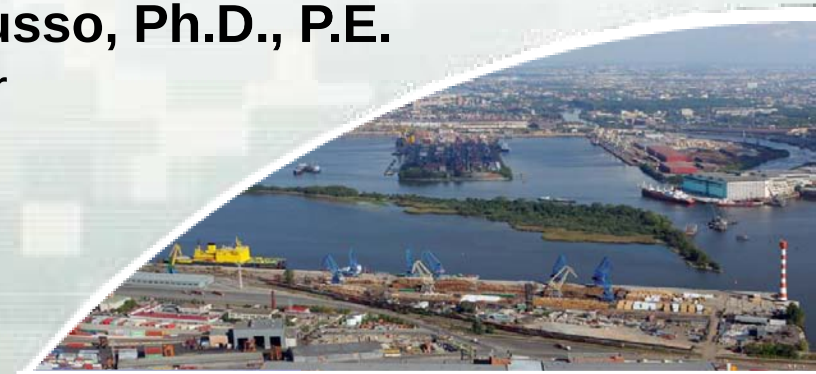

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Presentation Outline

- Background on development of the methodology.
- Introduction: Bayesian networks (Bns) in general.
- Application: Evaluate performance of infrastructure networks at commercial ports.
- Demonstration: Impact of sea-level rise on operational performance (reliability of at-berth support services).
  - Evaluate performance under different sea-level rise scenarios.
  - Evaluate the impacts or benefits of modifying the infrastructure network.

Systems Thinking in Operations: Developing a Long-term Investment Strategy with Respect to Sea-level Rise

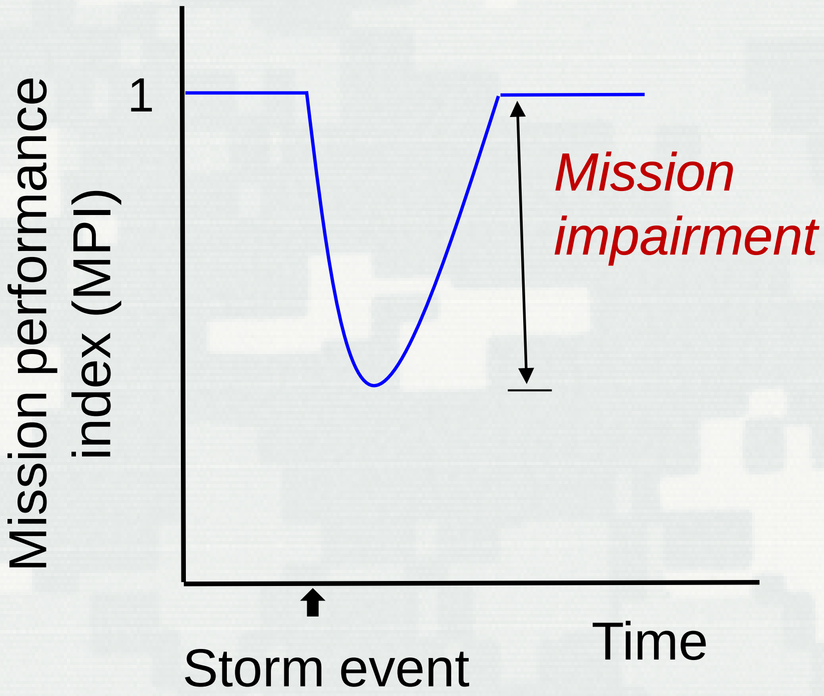
Problem: Rising sea-levels will increase the level of damage caused by coastal storms to transportation infrastructure. What effect will increases in sea-level have on the performance and reliability of port operations?

Study Approach: Quantify the risks posed by coastal storms to infrastructure supporting operations and determine how changes in sea-level would affect those risks.

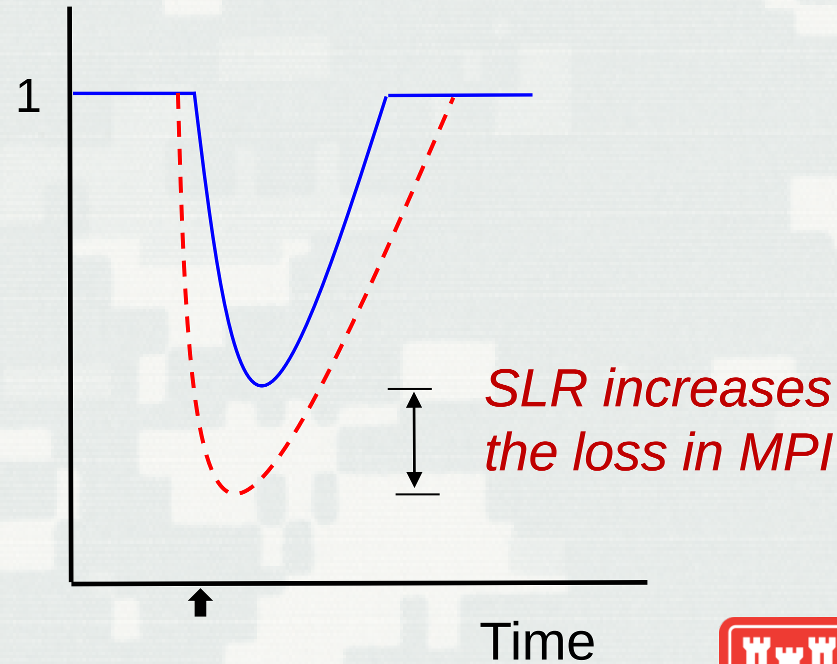
Performance Metric: Probability that support services to ships at-berth will not be interrupted at least once a year by a coastal storm.

Coastal storms can impair the level of mission performance.

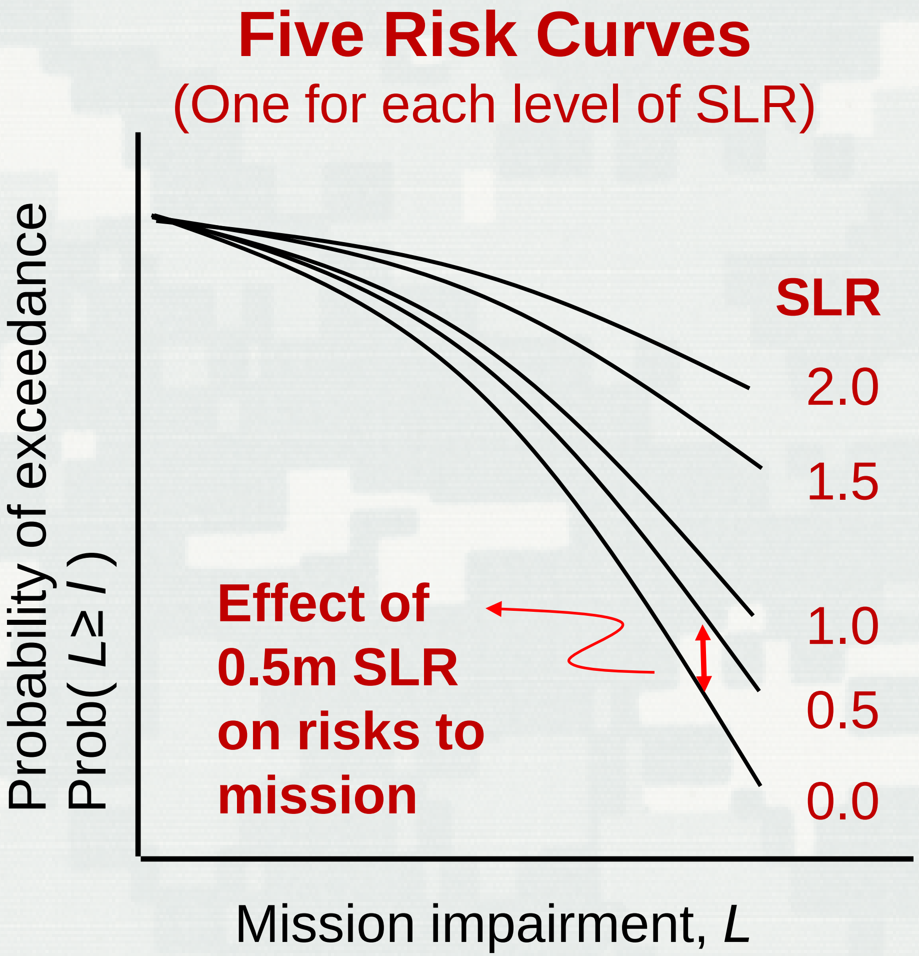
Mission impairment is a loss in mission performance.



Sea level rise (SLR) can affect the level of impairment caused by a storm of severity x.



Risk assessment determines how SLR affects the probability of losses in MPI.



Potential losses are expressed as some agreed-upon measure of mission impairment, *L*.

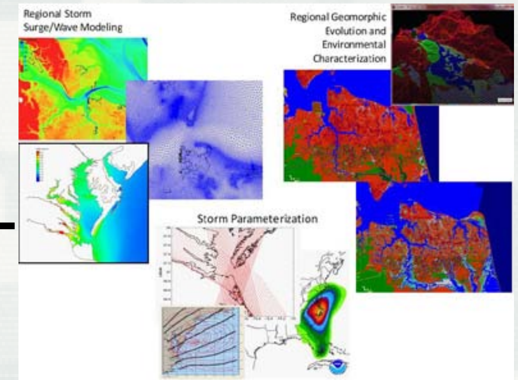
Prob(*L*≥*l*) : Probability that the level of mission impairment is greater than or equal to level *L*=*l*.

SERDP RC-1701 Study Approach

Infrastructure Inventory

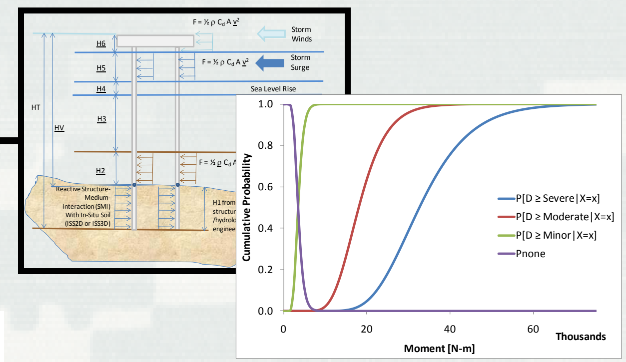
Geographic Inf. System (GIS)

Coastal Storm Models

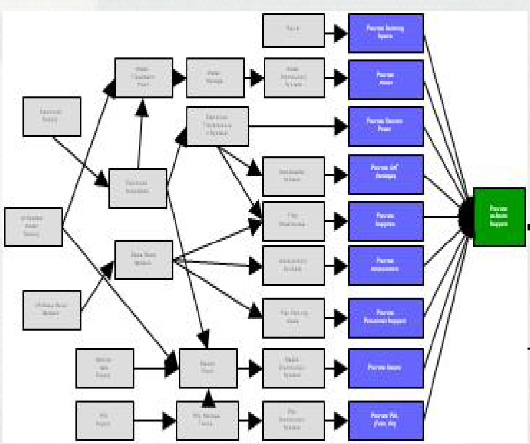


TC96
ADCIRC
SWAN
CMS
GSSHA

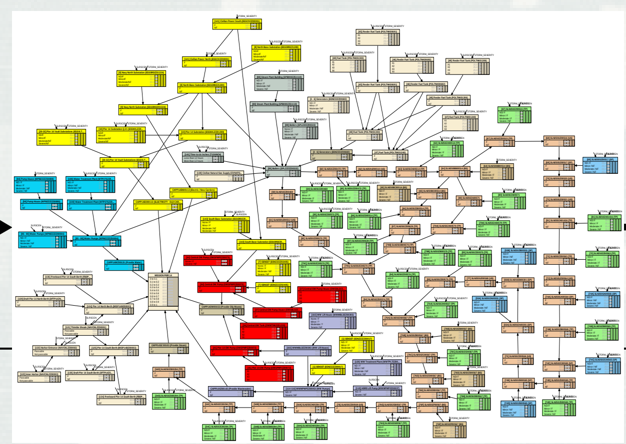
Structural Reliability Analysis



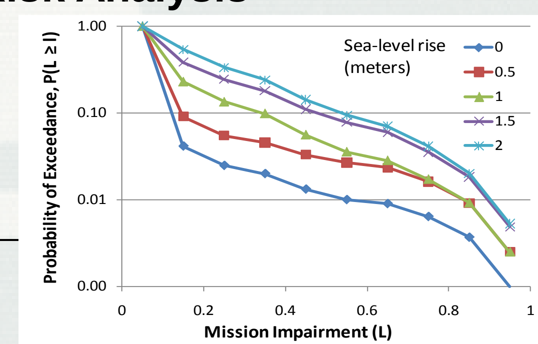
Mission Decomposition



Bayesian Network Model



Risk Analysis



Strategic Environmental Research and Development Program (SERDP RC-1701) Study Participants*

- **Coastal Storm Modeling:** Jane Smith, Jay Ratcliff, Honghai Li, Lihwa Lin, Cary Talbot, Mike Follum
- **Geomorphologic Modeling:** Andrew Morang
- **Environmental Modeling:** Craig Fischenich, Kyle McKay
- **Mission Decomposition:** Michael Case, Steve Pranger
- **Structural Analysis:** Jose Rullan-Rodriguez, Paul Mlakar
- **Geographic Information Systems** Scott Bourne
- **Risk Assessment:** Martin Schultz
- **Project Management:** Edmond Russo, Kelly Burks-Copes

* All participants affiliated with USACE Engineer Research and Development Center (ERDC).

Caveats for Public Release

- No information about Naval Station Norfolk is being revealed in this presentation.
- The purpose of this presentation is to describe how the risk assessment method could be applied at a commercial port.
- The infrastructure network has been modified:
  - Location and elevation of assets have been changed.
  - Network topology has been modified.
  - Network adapted for the mission to provide at-berth support for ships atr commercial ports.
- The results demonstrate what types of insight this approach can provide.

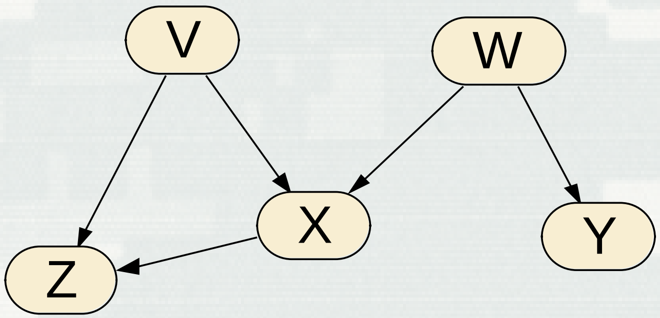
What are Bayesian Networks (Bn)?

- Factorization of a joint probability distribution over random variables.
- A Bn consists of two parts:
  - A graphical model, and
  - A set of conditional probability tables.
- Developed for probabilistic reasoning:
  - Predictive inference: Reasoning from causes to effects.
  - Diagnostic inference: Reasoning from effects to causes.
- Objective: Estimate the probability of random variable states and update probabilities with new information.

The graphical model shows causal influence among random variables.

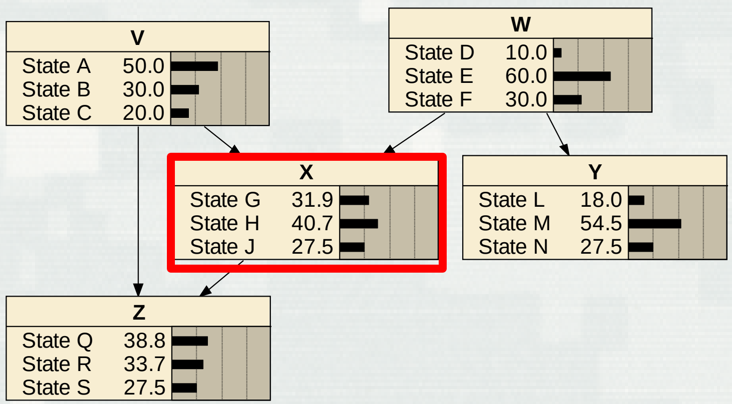
- A graphical model consists of nodes and edges.
  - Nodes are random variables - well-specified events or components of a system.
  - Edges signify causal influence between variables.
- In a directed acyclic graph, influence flows in one direction through the network.
- Any joint probability distribution can be represented as a DAG.

A DAG with five random variables.



Graphs can be developed from blueprints, flow charts, diagrams, or expert knowledge.

Nodes are parameterized using conditional probability tables (CPTs).



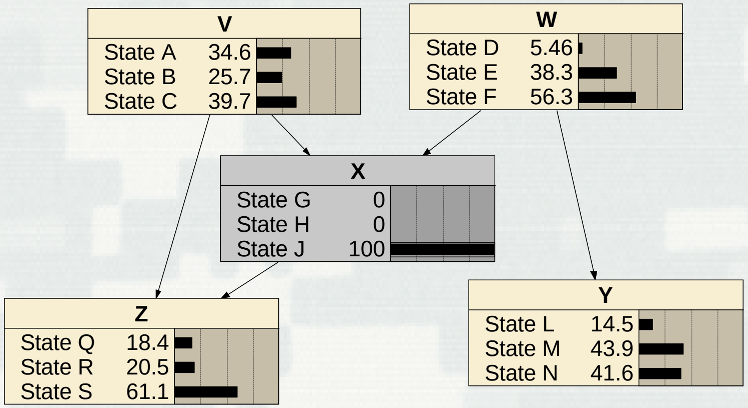
Sample CPT for random variable X

State of		State of X		
W	V	G	H	I
A	D	0.8	0.1	0.1
A	E	0.45	0.45	0.1
A	F	0.4	0.2	0.4
B	D	0.45	0.45	0.1
B	E	0.15	0.7	0.15
B	F	0.1	0.45	0.45
C	D	0.35	0.3	0.35
C	E	0.2	0.4	0.4
C	F	0.05	0.05	0.9

- CPTs specify the conditional probability of each random variable state given the potential states of parent nodes.
- The Bayesian network computes the marginal probability of random variable states.
- Parameterization can be a challenging task.

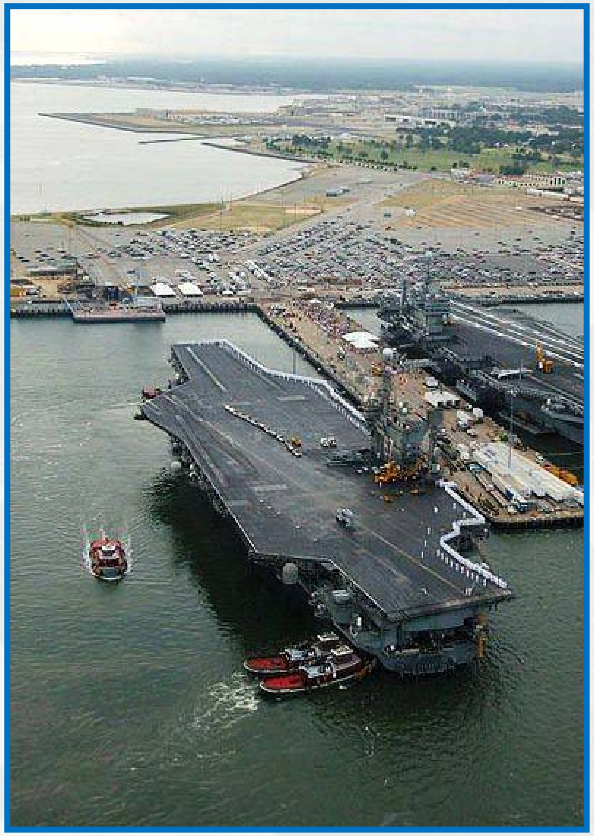
Statistical inference is accomplished by applying information to the model.

- Information may be hard (certain) or soft (uncertain).
- Bayesian updating is used to compute the posterior marginal probabilities of random variable states given the information.
- Example: By applying hard information that random variable X is in state J, the probability of all other random variable states are updated.



Modeling risks to infrastructure networks and mission performance at coastal sites.

- Identify a mission of interest
- Decompose the mission into capabilities and physical assets.
- Determine functional dependencies among physical assets.
- Model the reliability of assets that are subject to storm loads.
- Develop the graph and populate the conditional probability tables.



Capabilities commonly required for at-berth support of commercial ships.

<u>Utility services</u>

- Electricity to ships.
- Potable water.
- Wastewater and Oily waste.
- Steam.
- Navigation access and berths.

<u>Other services</u>

- Cargo handling
- Inter-modal transfer (Rail)

Each infrastructure sub-system is decomposed into well-defined assets.

STEAM

- Steam plant building
- Steam plant pumps and mechanicals
- Steam distribution lines

WASTEWATER

- Wastewater pumps
- Wastewater lift building
- Wastewater treatment plant

OILY WASTE

- Oily wastewater tank
- Oily wastewater pumps
- Oily wastewater pump building

WATER

- Potable water treatment plant
- Water pumps and pump building

ELECTRICAL

- Electric substations & transformers
- Backup generators and fuel tanks

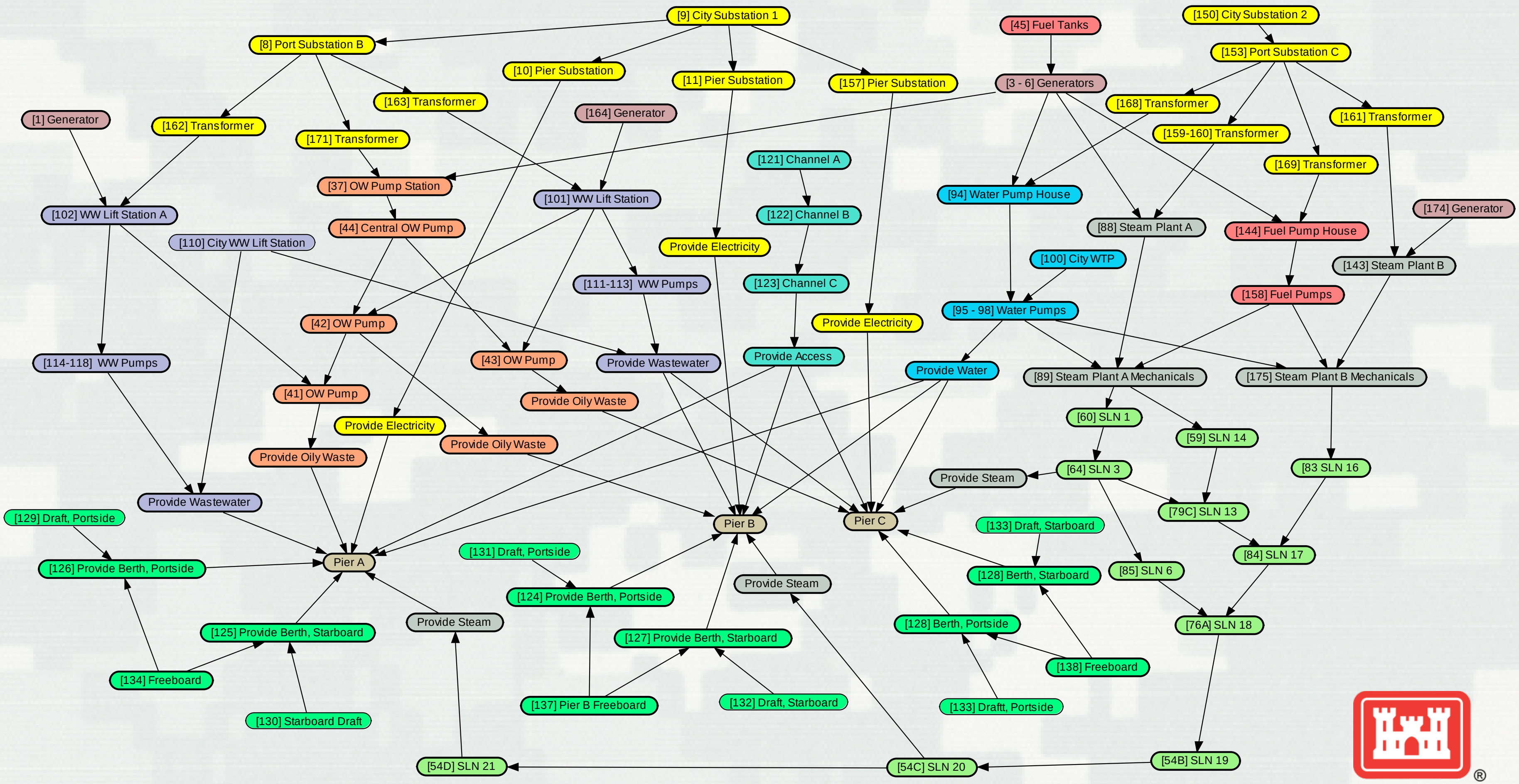
NAVIGATION

- Navigation channels
- Draft and freeboard at berths

Each asset is defined by:

1. **Location**
2. **Potential damage states**
3. **Damage function**
4. **Fragility curve**
5. **Connectivity**

Map dependencies among physical assets in the infrastructure network.



The Bayesian network contains five types of random variables.

Risk Drivers

Sea-level rise (m) (5 scenarios)
Storm severity (3-level index)

Asset Damage State

Two to four potential states for each asset.

Asset Functionality

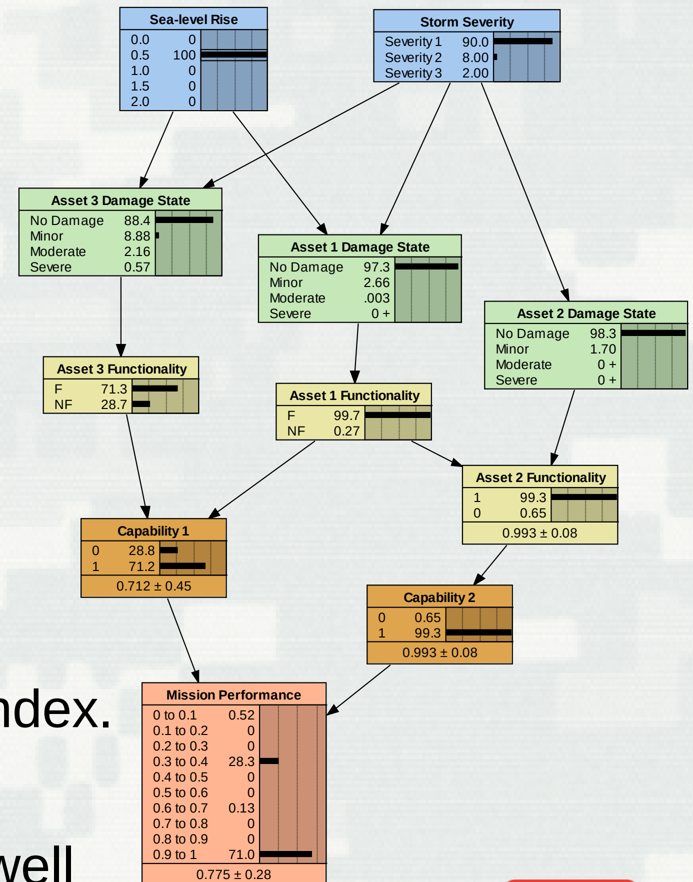
F = Functional / NF = Non-functional

Capability

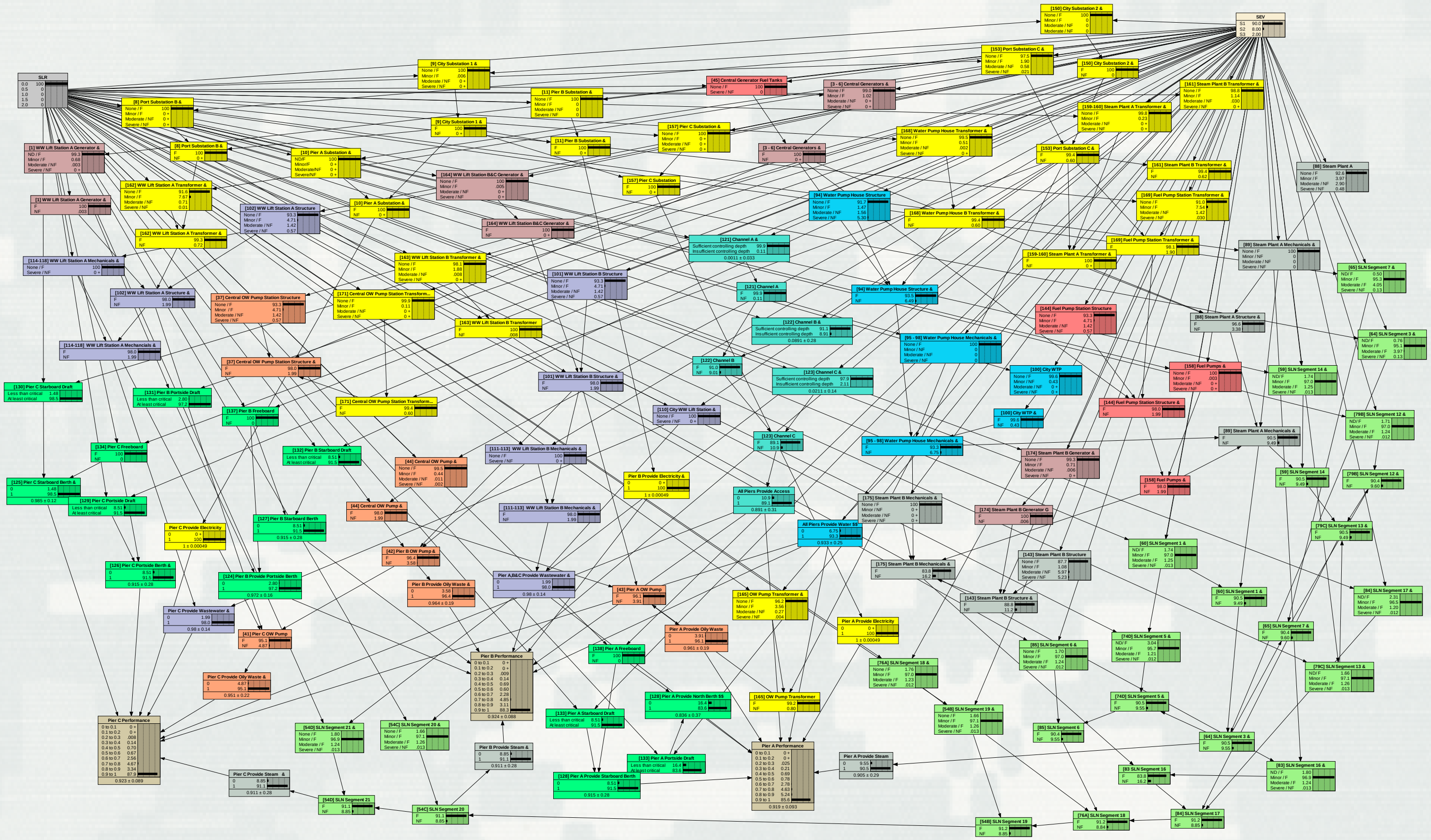
0 = No capability / 1 = Capable
Transforms the function node to a capability index.

Mission Performance

An agreed-upon function that describes how well the mission is performed.



Bayesian Network for Risk Assessment



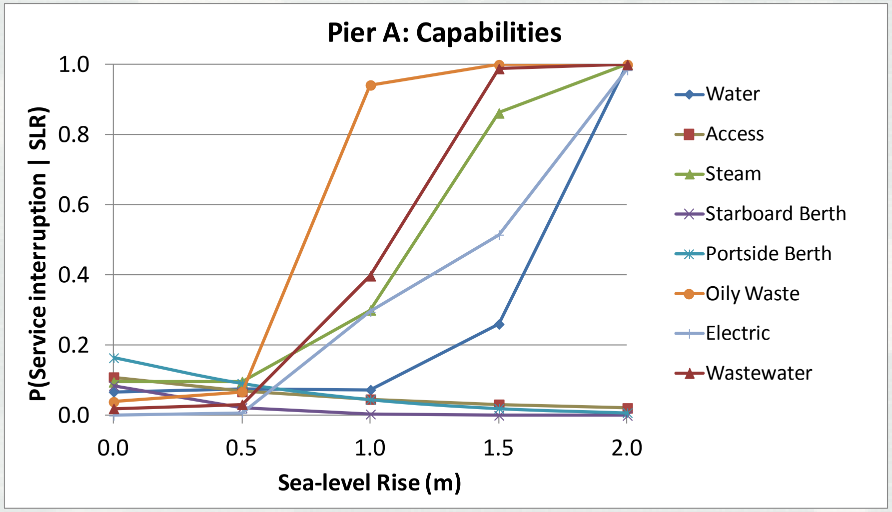
140 Nodes, 287 Edges, 11,744 Probabilities

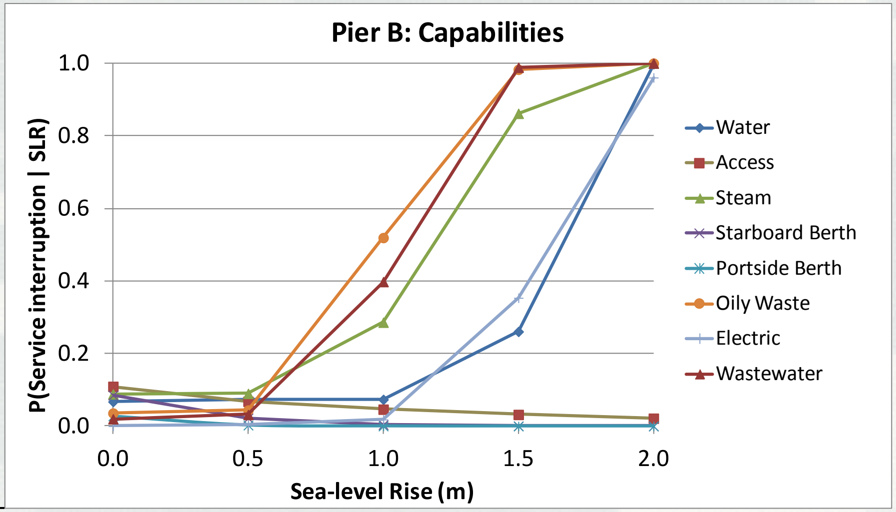
The model is used for inference about the infrastructure system and management.

- Post-storm reconnaissance: Diagnostic inference to predict asset damage states and functionality.
- Risk assessment: Predictive inference to characterize uncertainty in capabilities and mission performance.
- Evaluate adaptations to SLR: How would changes in the network topology or asset reliability affect capabilities and mission performance.
- Value of information analysis: Identify where better information about the reliability of assets should be obtained.

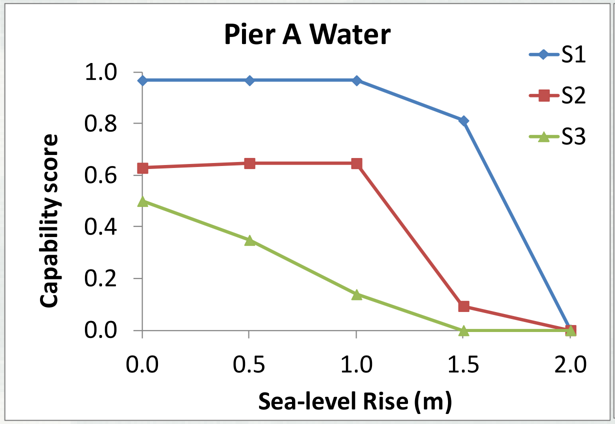
Effect of Sea-level Rise on Capabilities

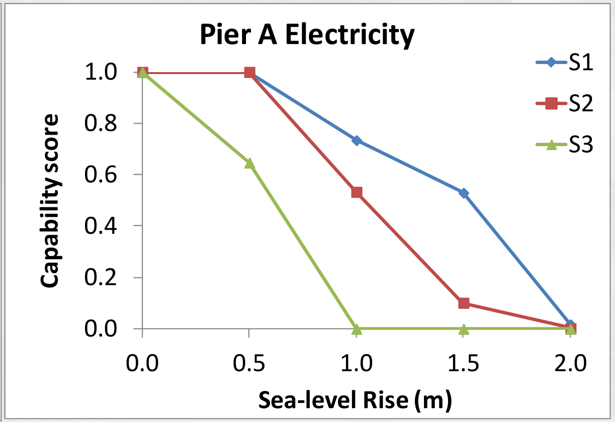
- Probabilities increase between 0.5 and 1.5 m SLR.
- Oily waste and wastewater systems are the first to be affected.
- Capabilities Provide oily waste and Provide electricity have lower reliability at Pier A than Pier B.
- Navigation and berthing capabilities improve as sea-level rises.

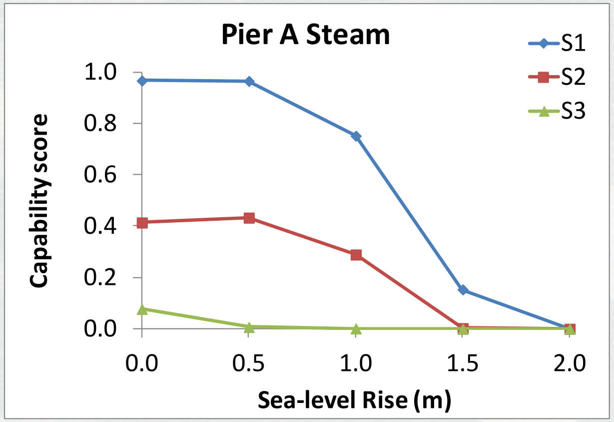


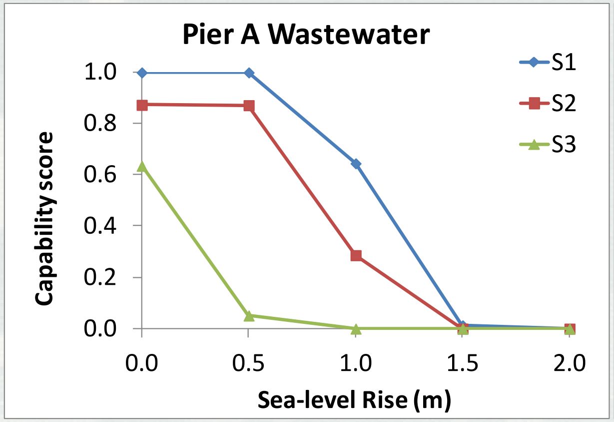


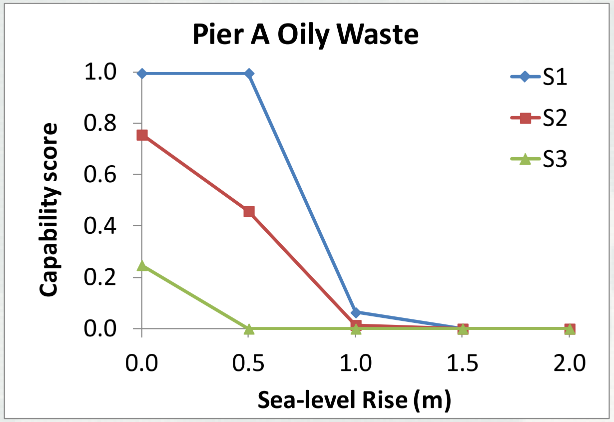
Capability Scores by Storm Severity











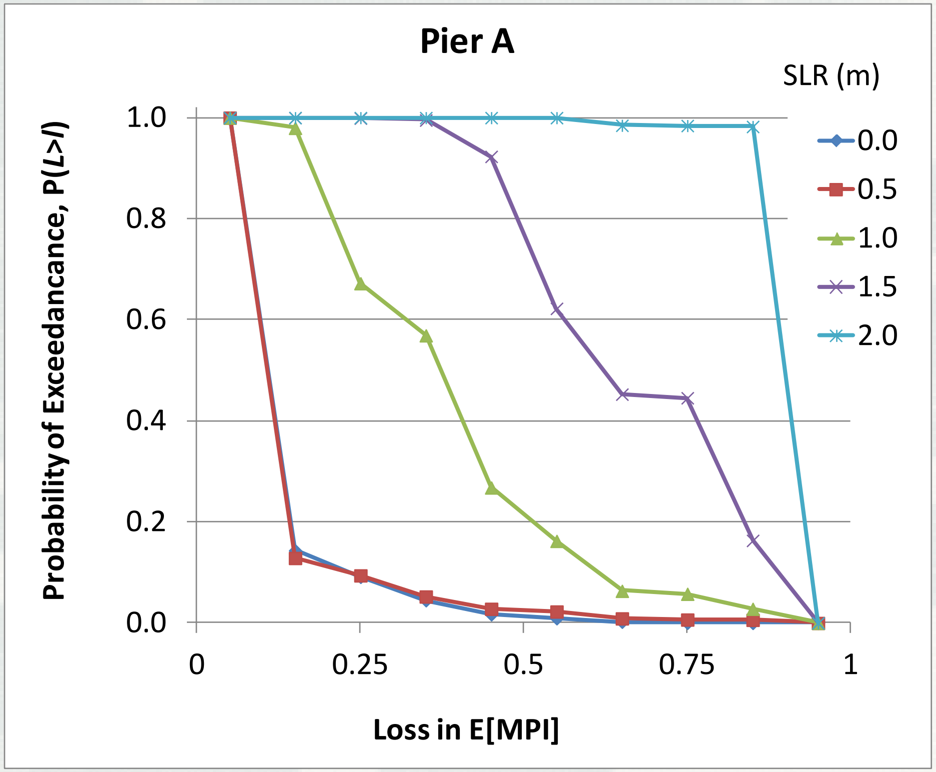
Capability score is the probability that a capability will not be interrupted.

At What Change in Sea-level will Mission Performance Degrade?

- The MPI is a multiattribute value function ($0 \leq MPI \leq 1$).
- w = Relative importance of each capability.
- C = Capability score

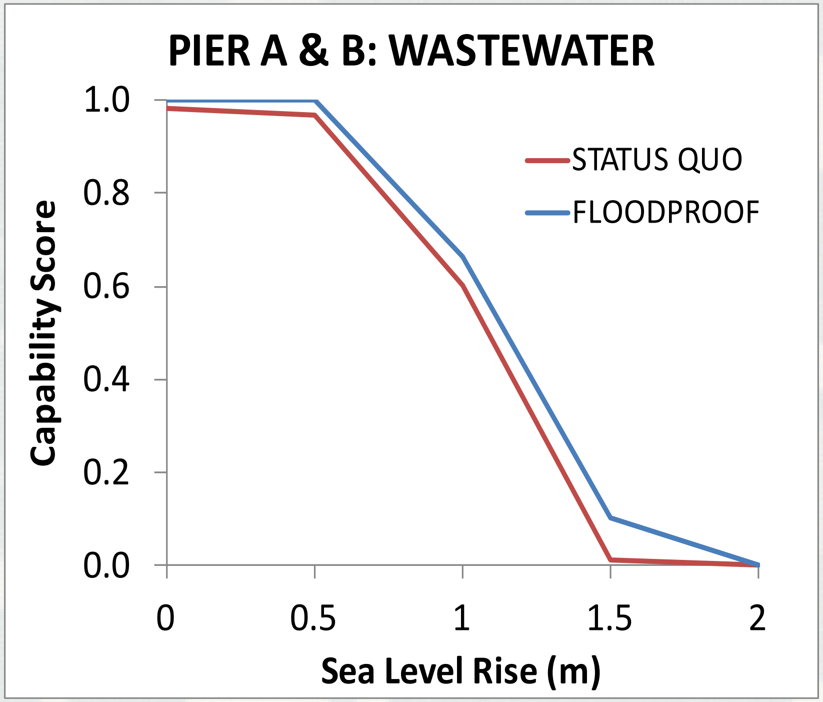
$$MPI_j = \sum_i w_{ij} C_{ij}$$

- LEC gives probability that a loss will exceed a level, $L>l$.
- Tipping point: The SLR at which the LEC transitions from concave to convex.



The Bayesian network provides a platform for experiments in SLR adaptation.

- Flood-proofing of wastewater infrastructure at Piers A&B (*Pumps, generators, building, transformer*).
- Flood-proofing increases the capability score to 1.0 only up to 0.5 m of SLR.
- Benefits of flood-proofing are limited by dependencies on other assets.
- Benefits tend to diminish w/ SLR.
- Piece-meal approach vs. whole-system approach to adaptation.



Conclusions

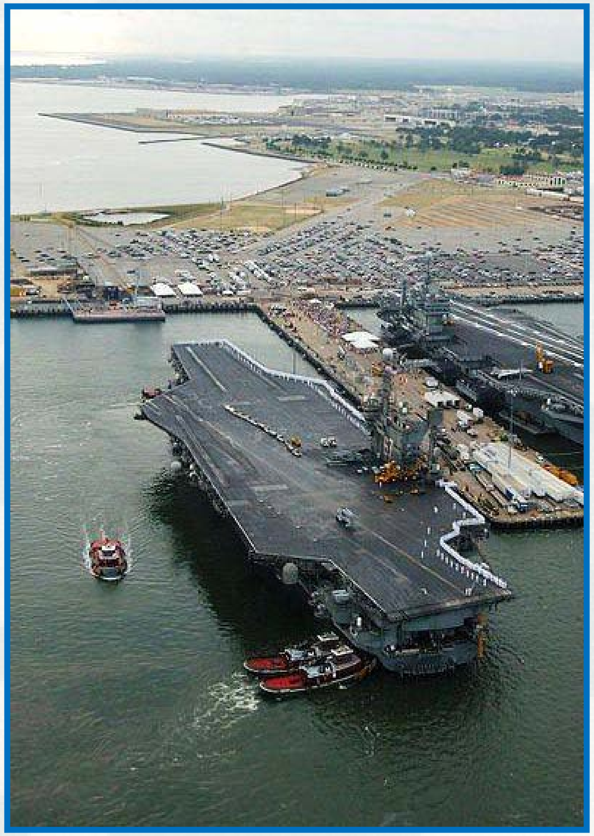
- Bayesian networks are a useful tool for modeling the performance of infrastructure networks.
- Method is scalable and adaptable. Can model highly complex joint probability distributions.
- Practical insights from applications:
  - Network-scale remedies will be needed to avoid potential losses in mission performance from SLR.
  - Selective redundancies and improvements in reliability may not be cost effective.

BACKUPS

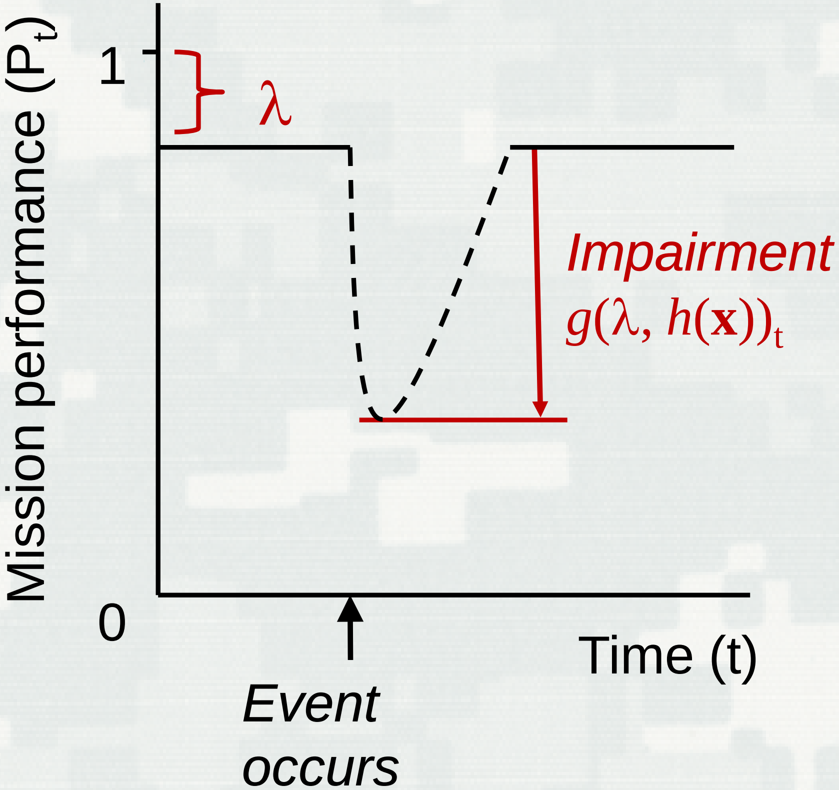
Bns can be used to model risks to the performance of infrastructure networks.

Five well-defined operational missions at NAVSTA Norfolk

1. Airfield
2. Heliport
3. Training
4. Command and control
5. Port operations
    1. Provide utilities to ships at berth.
    2. Provide crew life support (e.g., food, shower, laundry) and logistical support (parking).
    3. Provide maintenance dredging for berths and navigation channels.
    4. Provide ship repair and maintenance service.
    5. Provide logistics for supplies.
    6. Provide ammunition for small arms.



Natural hazards can impair the level of mission performance.



Performance function:

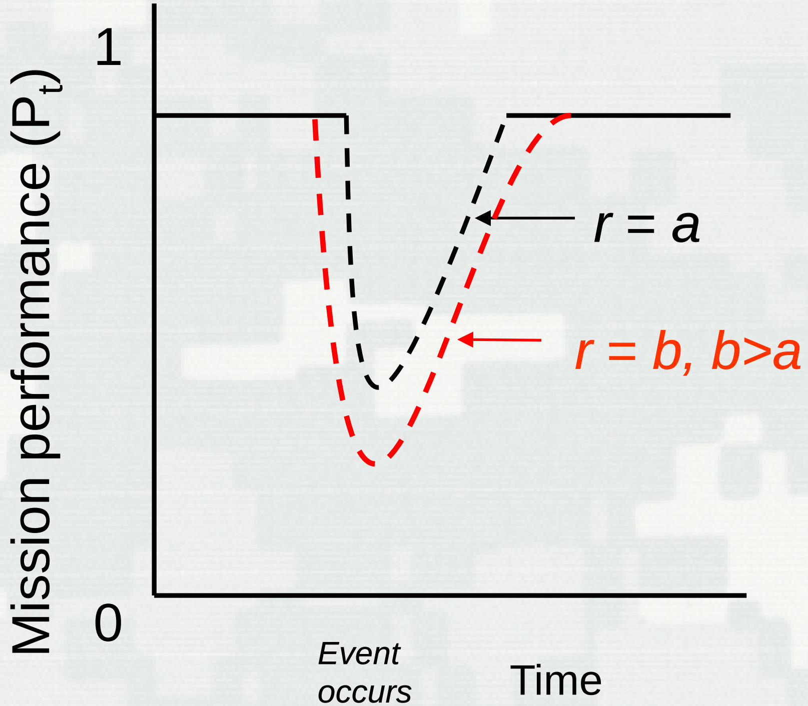
$$P_t = P - g\left(\lambda, h\left(r, \mathbf{x}\right)\right)_t$$

- $g(\lambda, h(r, \mathbf{x}))_t$: Impairment
- λ : Potential improvement
- $h(r, \mathbf{x})$: Event severity
- r : Sea-level rise (meters)
- $\mathbf{x}$: Determinants of event severity
  - Pressure, radius, speed, *etc.*

Loss function:

$$L = \sum_t g\left(\lambda, h\left(r, x\right)\right)_t$$

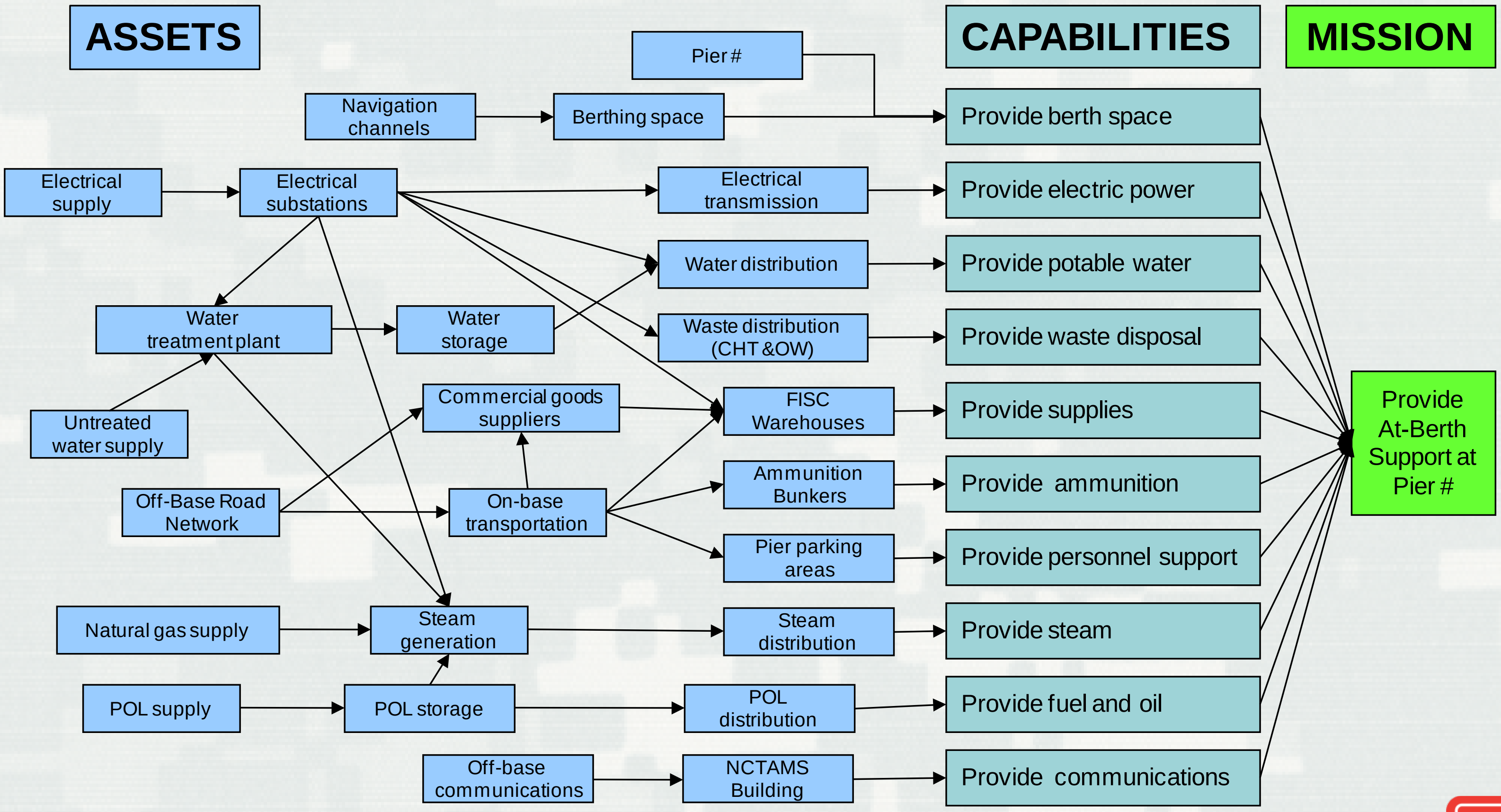
Sea level rise can affect the level of impairment caused by a storm of severity **x**.



$$P_t = P - g\left(\lambda, h\left(r, \mathbf{x}\right)\right)_t$$

- r : sea-level rise (meters)
- $\{a,b\}$ are realizations of r

Develop an Asset Capability Network (ACN) describing how the mission is performed.

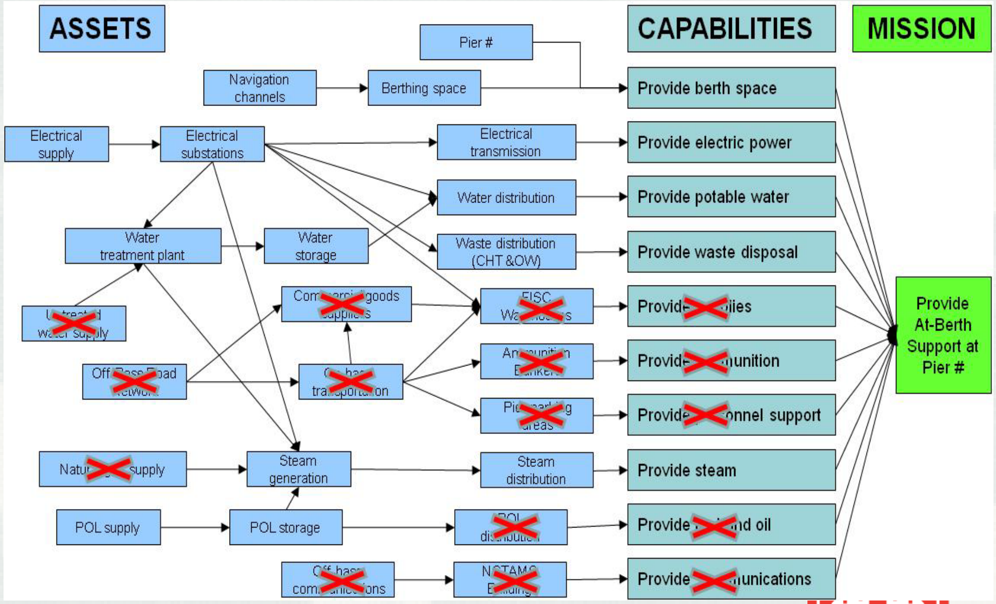


Some systems are eliminated from the network.

Potential reasons for elimination included:

1. Physical assets that comprise the system do not appear vulnerable to damage from coastal storms.

2. A method of assessing damages based on the modeled loadings from coastal storms could not be found.



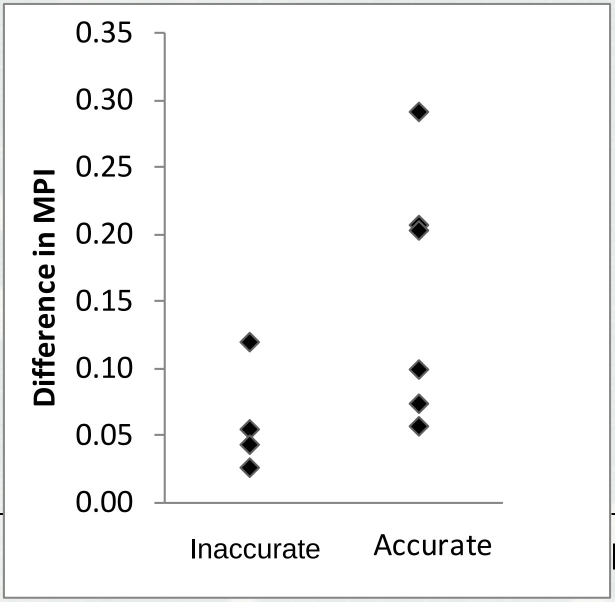
3. The physical assets were located beyond the limits of the model domain.

Mobile assets and personnel are not considered in this analysis.

Swing weights were obtained from the Ship Support Officer, NSN

Capability	Pier	
	11	12 & 14
Provide Electric Power	0.230	0.217
Provide Wastewater	0.230	0.217
Provide Steam	0.172	0.163
Provide Potable Water	0.115	0.109
Provide Oily Waste	0.115	0.109
Provide Access	0.080	0.076
Provide North Berth	0.057	0.054
Provide South Berth	-	0.054

- Ten pairs of performance scenarios were randomly generated. Respondent chose the scenario with the highest level of performance.
- 60% of MPI predictions using swing weights agreed with respondents choices.
- Inaccurate predictions were associated with harder choices (smaller differences in MPI).

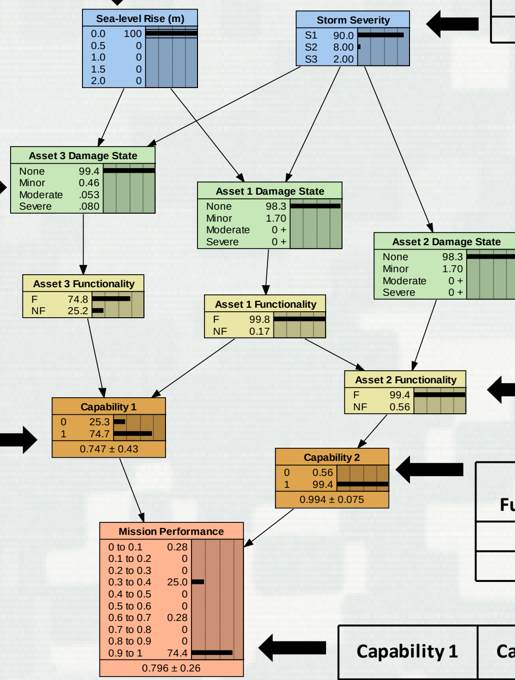


The graphical model is parameterized with marginal and conditional probability tables.

SLR	SEV	Asset 3 Damage State			
		None	Minor	Moderate	Severe
0.0	S1	9.98E-01	9.27E-04	2.13E-04	6.60E-04
0.0	S2	9.71E-01	2.46E-02	2.53E-03	1.82E-03
0.0	S3	9.01E-01	8.89E-02	6.99E-03	3.22E-03
0.5	S1	9.75E-01	2.09E-02	2.24E-03	1.71E-03
0.5	S2	7.76E-02	7.55E-01	1.39E-01	2.79E-02
0.5	S3	2.77E-04	4.80E-01	4.24E-01	9.62E-02
1.0	S1	9.04E-01	8.63E-02	6.81E-03	3.17E-03
1.0	S2	9.46E-05	4.25E-01	4.64E-01	1.11E-01
1.0	S3	7.15E-12	4.46E-02	5.79E-01	3.77E-01
1.5	S1	6.75E-01	2.96E-01	2.19E-02	6.66E-03
1.5	S2	1.02E-11	4.71E-02	5.82E-01	3.71E-01
1.5	S3	0.00E+00	6.70E-05	1.69E-01	8.31E-01
2.0	S1	2.09E-01	6.89E-01	8.38E-02	1.80E-02
2.0	S2	0.00E+00	5.11E-05	1.59E-01	8.41E-01
2.0	S3	0.00E+00	1.49E-12	2.16E-03	9.98E-01

SLR: Sea-level Rise (m)				
0.0	0.5	1.0	1.5	2.0
0.20	0.20	0.20	0.20	0.20

SEV: Storm Severity Index		
S1	S2	S3
0.9	0.08	0.02



ASSET 1 Functionality	ASSET 2 Damage State	Asset 2 Functionality	
		F	NF
F	None	1.00	0.00
F	Minor	0.75	0.25
F	Moderate	0.25	0.75
F	Severe	0.00	1.00
NF	None	0.00	1.00
NF	Minor	0.00	1.00
NF	Moderate	0.00	1.00
NF	Severe	0.00	1.00

Asset 3 Functionality	Asset 2 Functionality	Capability 1
F	F	1
F	NF	0
NF	F	0
NF	NF	0

Asset 2 Functionality	Capability 2
F	1
NF	0

Capability 1	Capability 2	Mission Performance
0	0	0
0	1	0.35
1	0	0.65
1	1	1

Probabilities of asset damage states are from a structural reliability analysis.

Example: 250 psi steam lines on tall pylons

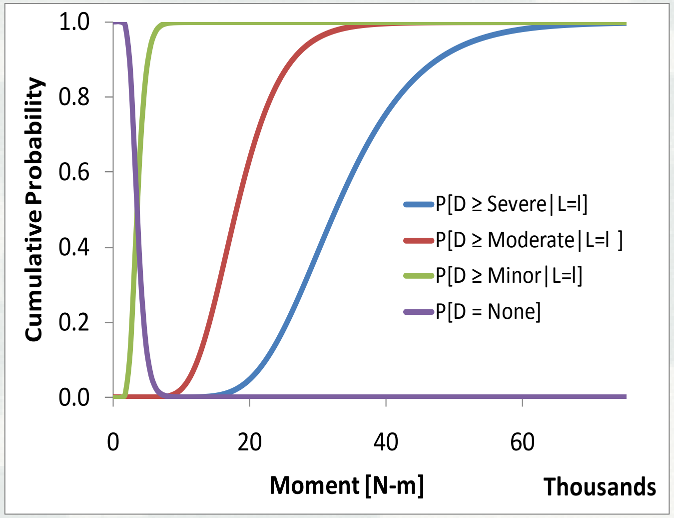
(A) Infrastructure is decomposed into SUAs

(A) Potential damage states are defined

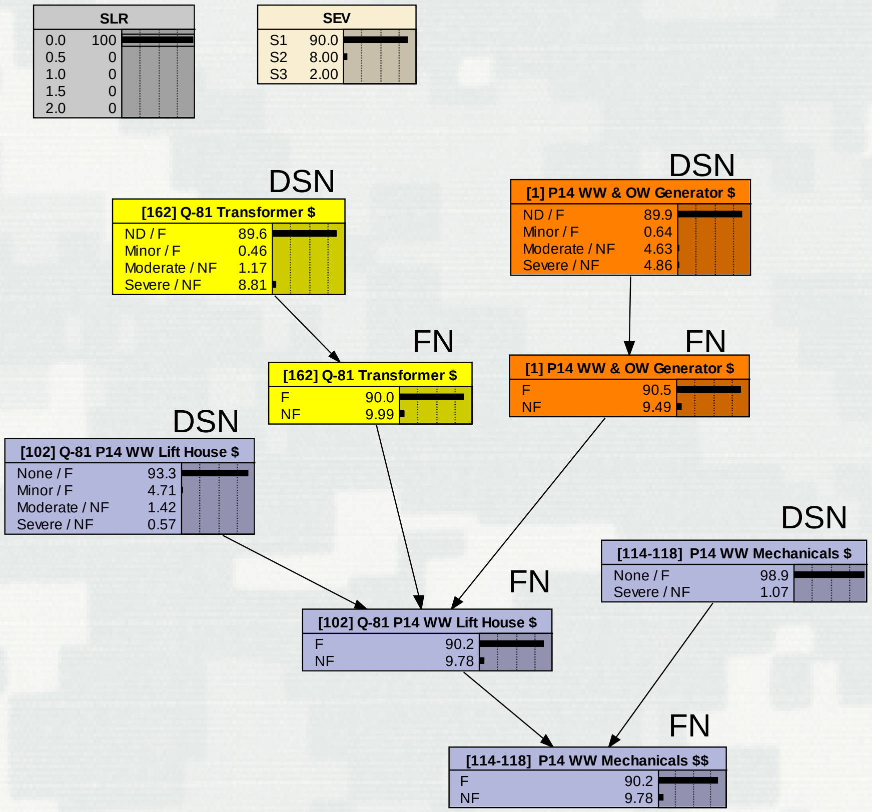
State	Description	Functional?
None	No damage.	Yes
Minor	Cracks in pylon. No visible damage to steam line.	Yes
Moderate	Pylon replacement required. No visible damage to steam line.	Yes
Severe	Pylon concrete crushed. Steam line has visible cracks.	No.

(B) Damage functions predict the response of the SUA to wind, water, and sediment loads.

(C) Fragility curves estimate the probability of each damage state as a function of the moment given the wind, water, and sediment loads acting on the SUA.



Asset Damage and Function Nodes

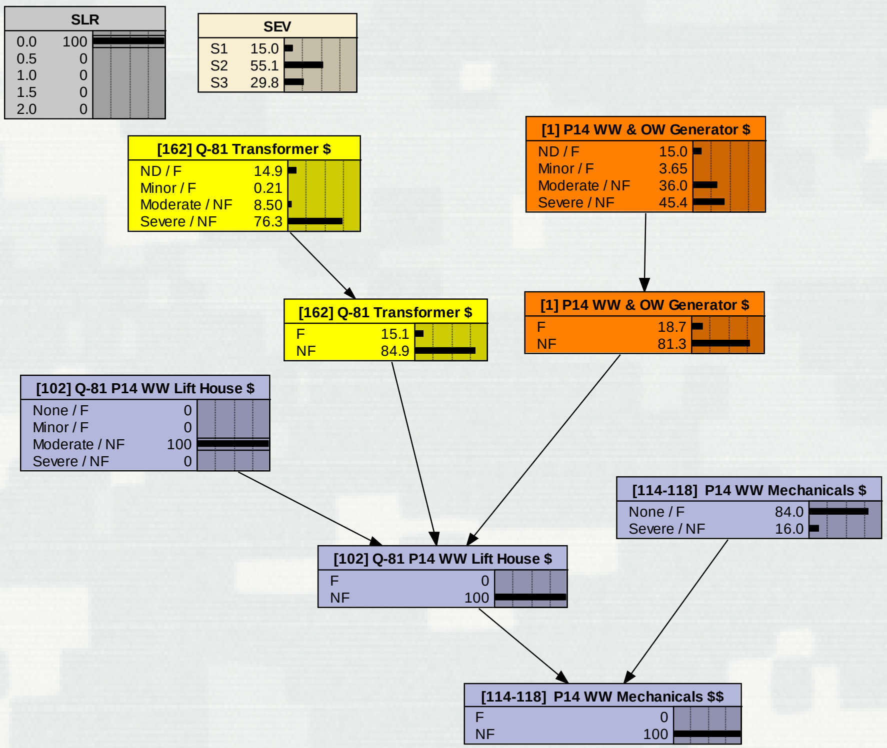


Subset of the network showing assets related to the capability to provide wastewater at Pier 14.

- Suppose SLR = 0.0 m.
- Each damage state node (DSN) is defined by two or more damage states.
- DSNs give the probability of that asset being in each potential damage state at least once in a year.*
- Function nodes (FN) give the annual probability of being non-functional at least once in a year.*
- SEV could be instantiated to estimate the annual probability of damages from a coastal storm of severity.

*The assumption that system states are caused by a coastal storms is implicit.

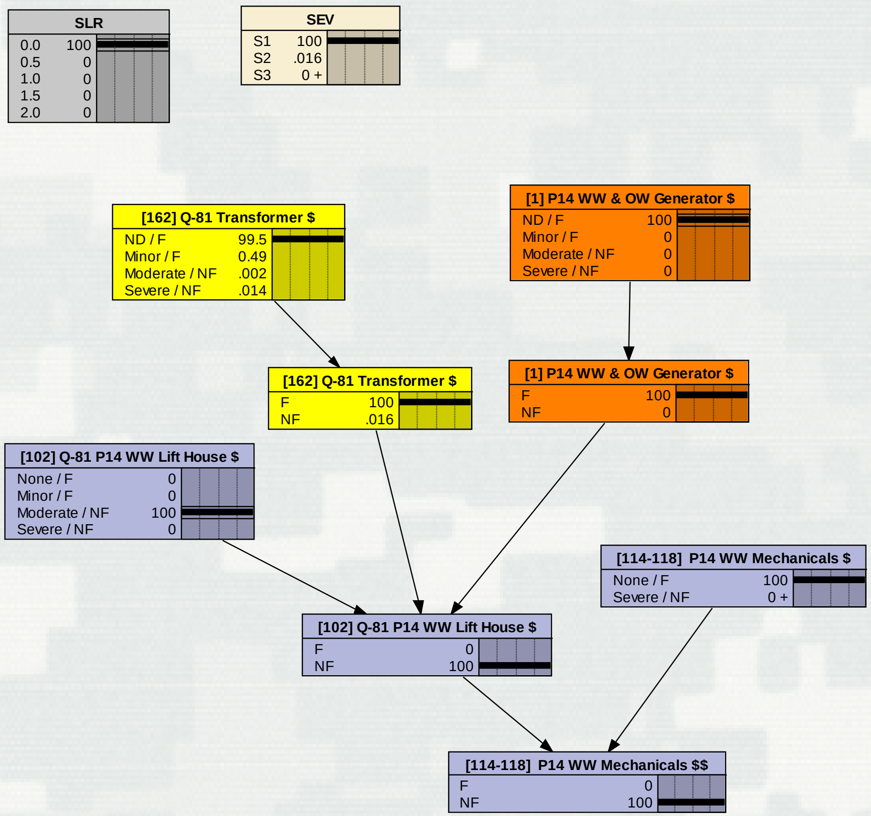
The model can be updated with observations of asset damage states.



An implicit assumption in the network is that damages are caused by a coastal storm. If an asset is observed to be damaged, then a storm must have occurred and caused those damages. If an asset is observed to be undamaged, then a storm must have occurred and the asset withstood the forcings.

- Suppose the damage state of the WW Lift House structure [102] is ***observed*** to be "Moderate / NF".
- The state of all other assets is ***un-observed***. Each unobserved DSN gives the probability that asset is in each of its potential damage states given knowledge of the state of [102].
- SEV node reports an inference about the storm that caused the damage to [102].
- Damage state probabilities can no longer be interpreted as "annual probabilities."

Additional observations can be used to apply more information to the model.



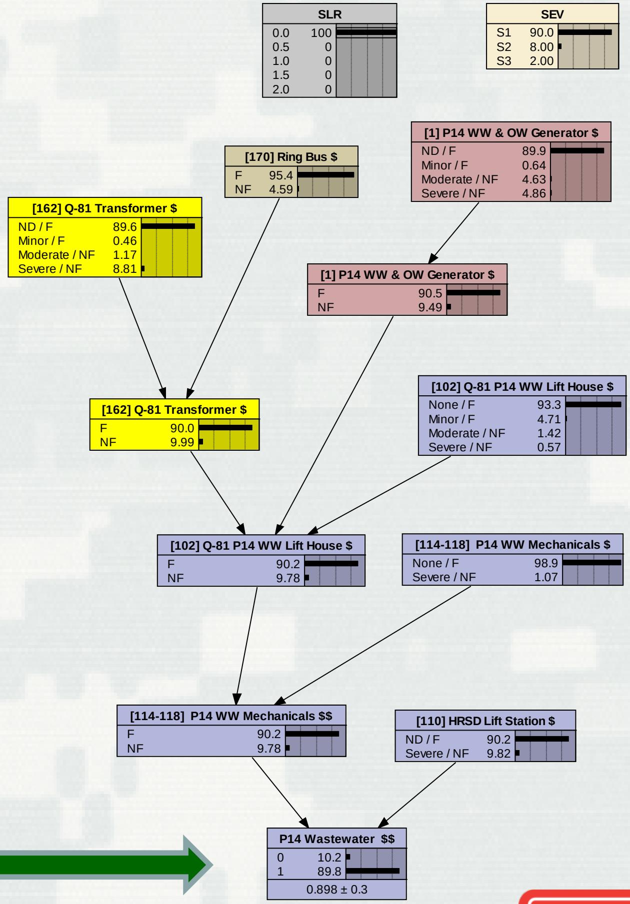
- Suppose that further investigation reveals that the P14 WW Generator [1] is not damaged.
- This leads to high confidence in the damage state and functionality of other assets, which remain unobserved.
- The SEV node reports an inference about the storm that caused the damage to [102].
- There is a high degree of confidence that damage to [102] was caused by an S1 storm.

Probability of NO Service Interruption

- Capability nodes transform information about asset damage state and function to a real-valued capability score between 0 and 1.

- The score is the probability that a service will *NOT* be interrupted by damages to assets from coastal storms (other than Nor'easters) at least once during the year.

- Capability scores provide no information on the duration of interruption, the failure that caused the interruption, or the extent or cost of repairs needed to remedy the interruption.



When SLR is instantiated and there are no other instantiations in the net, the capability node can be interpreted as an annual probability because the SLR prior distribution is consistent with return periods of modeled of coastal storms.

Mission Performance Index (MPI)

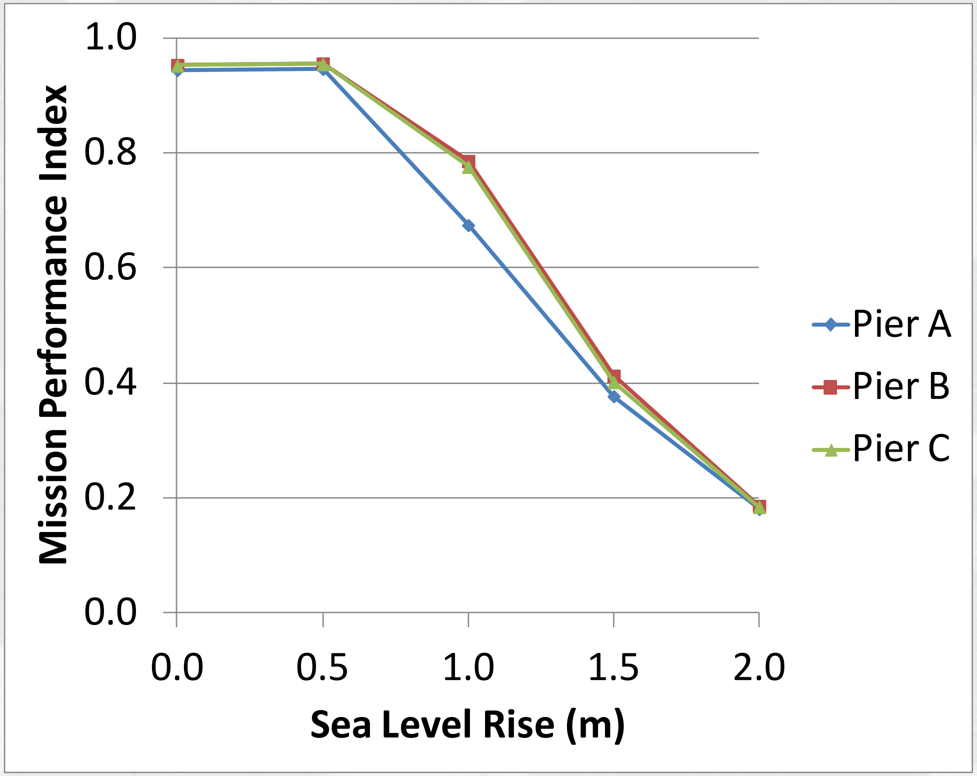
- The MPI is a multiattribute value function between 0 and 1.

$$MPI_j = \sum_i w_{ij} C_{ij}$$

- Weights (w): Relative importance of each capability with respect to management objectives at each pier. Obtain by swing weighting.
- Capability score (C): Probability a service will *NOT* be interrupted by damages to assets from coastal storms at least once during the year.
- MPI is a metric of overall mission performance for the infrastructure network, factoring in management objectives.
- Capability score is a performance metric for each capability.

Expected MPI decreases with SLR.

- Pier A has a lower E[MPI].
- E[MPI] at Pier A decreases with SLR at a slightly faster rate.
- E[MPI] at Piers B and C are almost equal.
- E[MPI] is most strongly affected between 0.5 and 1.0 m of SLR



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