Uncertainty Estimation of Historical Bathymetric Data from Bayesian Networks

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Objective and Approach

Objective

Produce a computationally efficient method for estimating bathymetric uncertainty of Naval Oceanographic Office DBDB-V* data

Approach

- Adapt Monte Carlo (MC) technique to Bayesian network (BN)
 - Lower computation costs and inputs
- Design and train network
 - Implement MC on sample sets
- Examine differences between MC & BN
 - Does this approach appear valid?

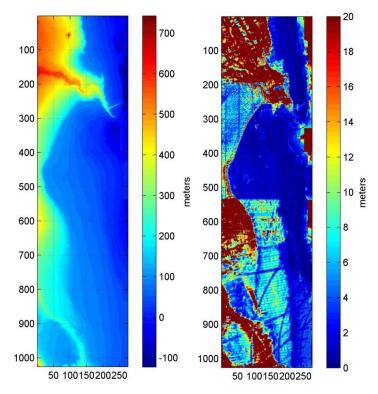
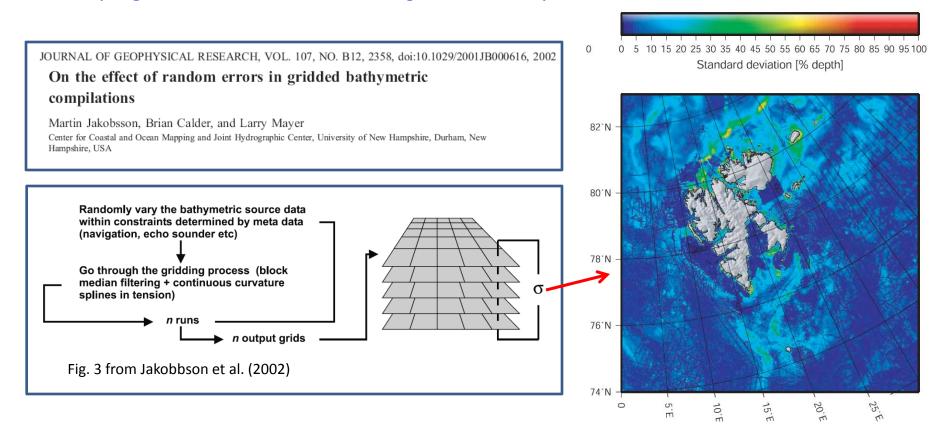


Figure: Fused bathymetry and uncertainty surfaces for the North Canyon Experiment (NCEX) data set. Units along the axis are pixels with each pixel being a 50 meter grid.

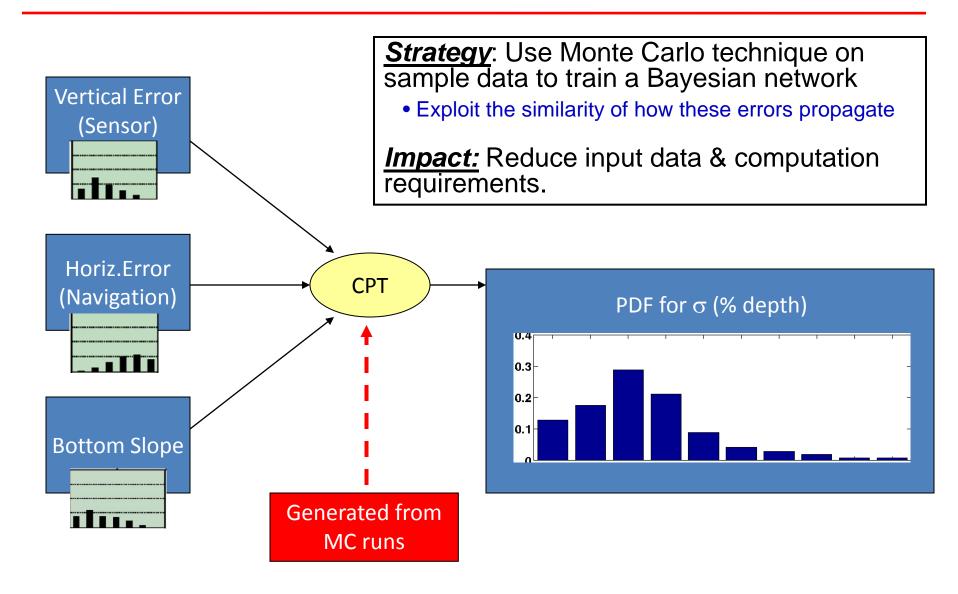
Background and Motivation

State-of-the-art for uncertainty estimation of historic bathymetry data is based on Monte Carlo (MC) procedures by Jakobbson, et. al. (2002)*

- Navigation error, bottom slope, & sensor accuracy -> depth uncertainty.
- Requires original soundings data very computationally intensive
- Not pragmatic to use on all soundings data held by NAVOCEANO.



Solution Strategy - Bayes Net Adaptation



Bayesian Network Training and Use

Train BN w/ Monte Carlo technique

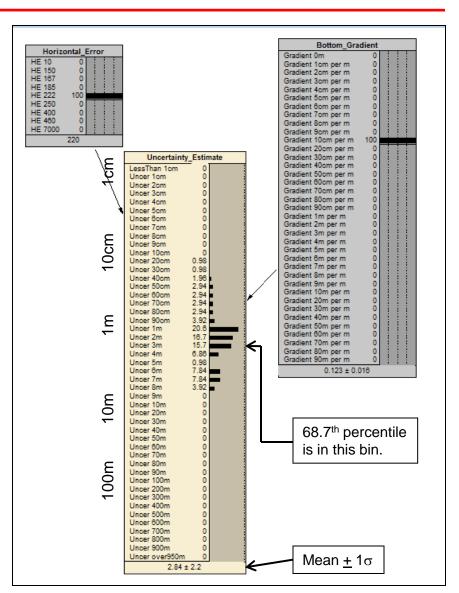
- 1. Tabulate applicable horizontal errors
- 2. Monte Carlo procedure on error categories
- 3. 2D histogram of possible uncertainties for CPT
- Repeat for each training area (Atlantic, Mariana Trench and Hawaii areas discussed here)

Example BN to right

- 1. Logarithmic scaling; one significant digit.
- 2. Uncertainty estimate: pick 68.7th quantile

Table I: Horizontal Error Categories

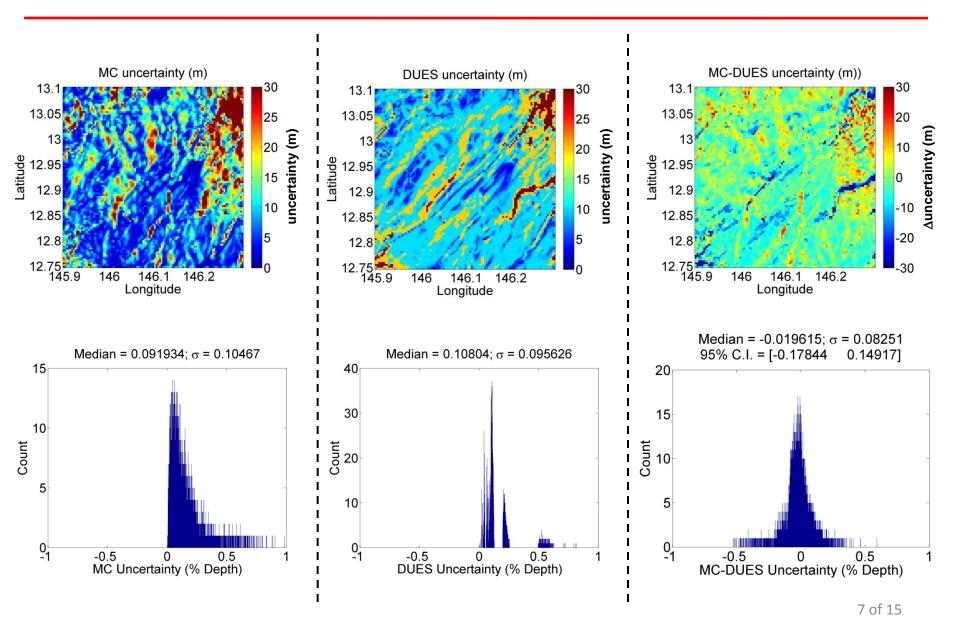
Navigation Mode	Accuracy	Navigation Mode	Accuracy
GPS/SINS (3 or more	10-15 m	NAVSAT/Single Range	250 m
Satellites)		LORAN/ SINS	
GPS/DR (3 or more	10-15 m	NAVSAT/ SINS	250 m
Satellites)			
NAVSAT/Range	150 m	NAVSAT/ Single Range	250 m
Range LORAN/SINS		LORAN /DR	
NAVSAT/Range	167 m	NAVSAT/DR	400 m
Range LORAN/DR			
NAVSAT/Hyperbolic	185 m	LORAN/ SINS	463 m
LORAN/SINS		LORAN/ DR	
NAVSAT/Hyperbolic	222 m	Satellite Altimetry	7000 m
LORAN/DR			



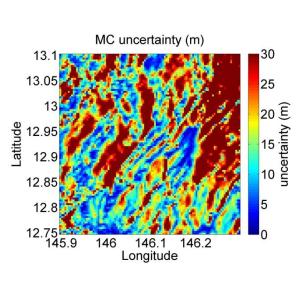
Training Area 1 – Mariana Trench

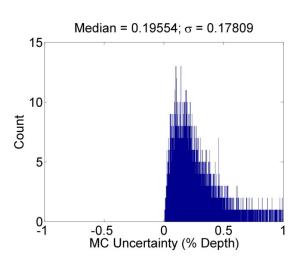
Small red box – training for 10-460 meter errors -1000 -2000 16 Large pink box – training for 7000 meter errors -3000 15 Latitude 13 -6000 -7000 11 -8000 18 -9000 -10000 16 142 152 146 150 Longitude 13.1 Latitude -8000 13.05 13 -8500 12.95 Tatitnde 12.9 10 -9000 12.9 -9500 12.85 12.8 -10000 12.75 145.9 145.95 146 146.05 146.1 146.15 146.2 146.25 146.3 142 150 152 140 144 146 148 Longitude Longitude

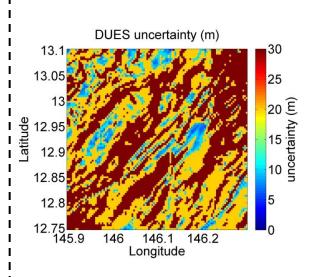
Training Area 1, 220m horizontal error

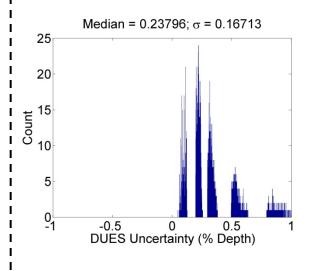


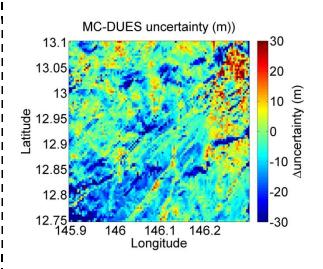
Training Area 1, 460m horizontal error

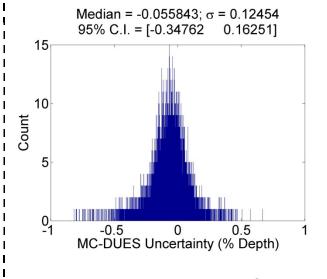




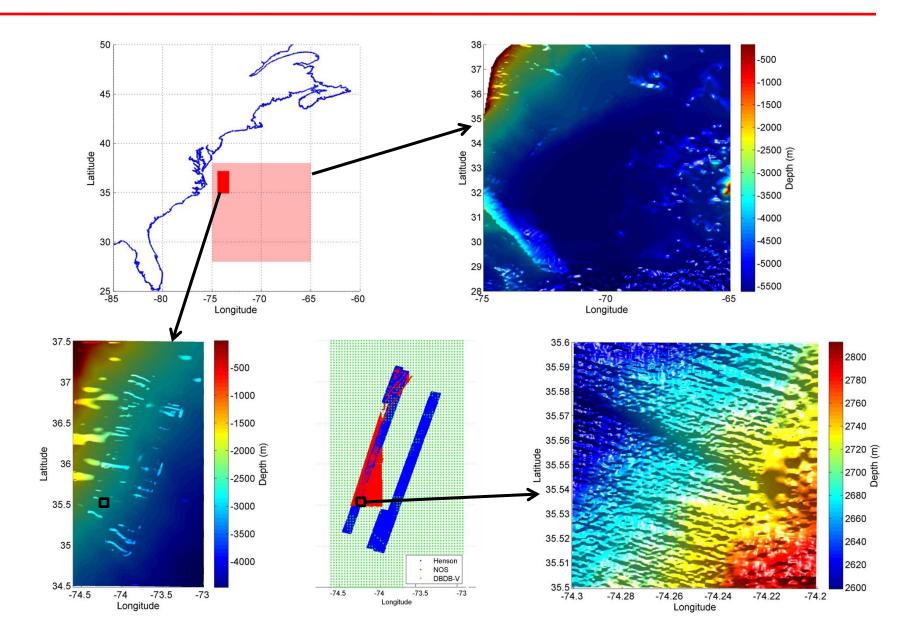




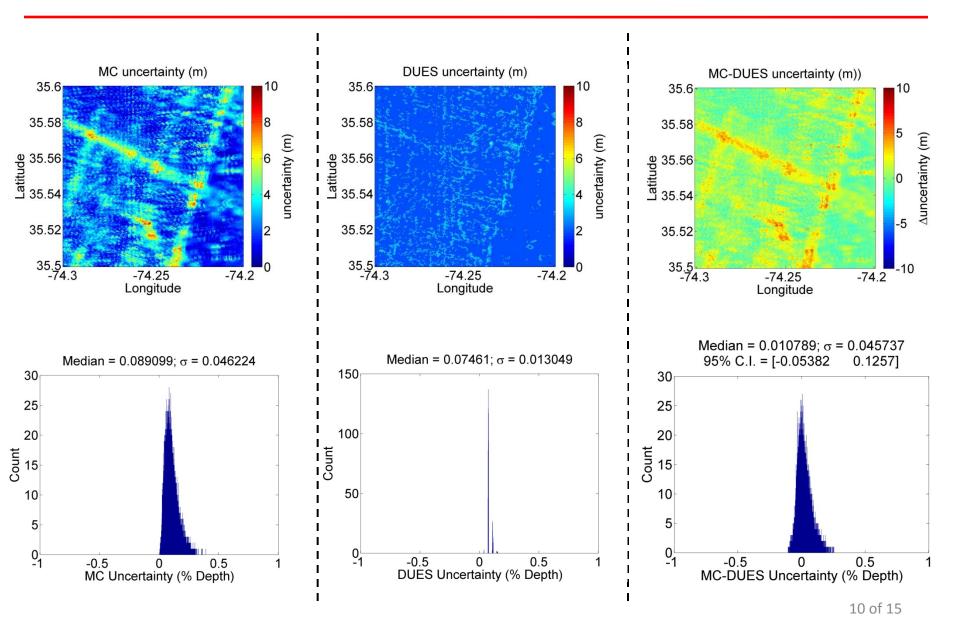




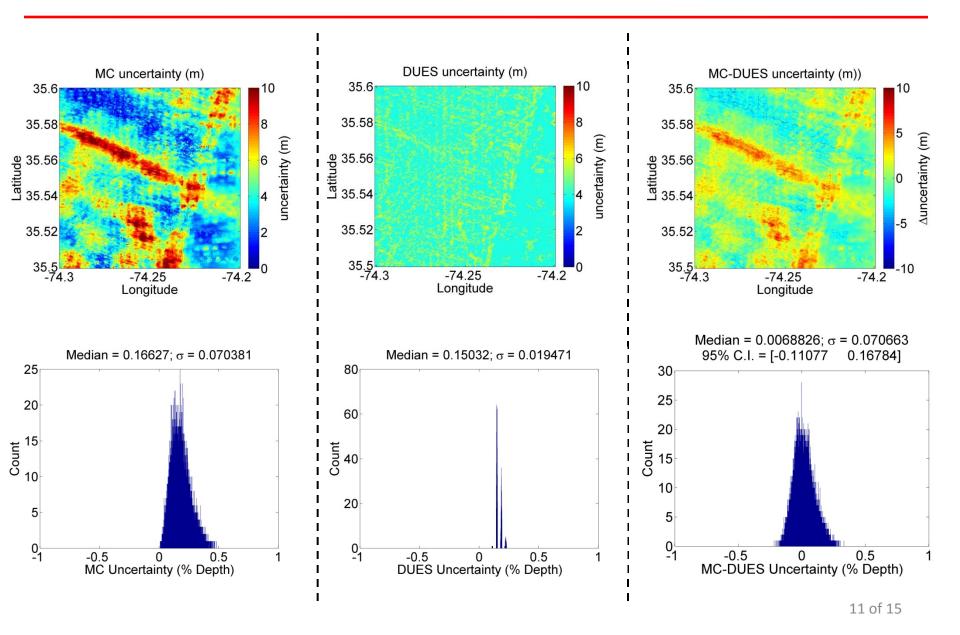
Training Area 2 – Atlantic Cont. Slope



Training Area 2, 220m horizontal error

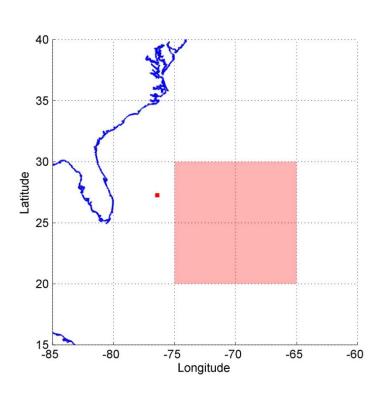


Training Area 2, 460m horizontal error

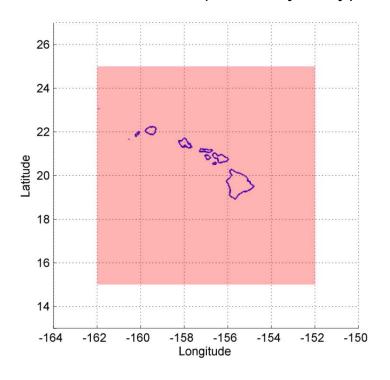


Training Areas 3 & 4

Training Area 3 - Atlantic Basin



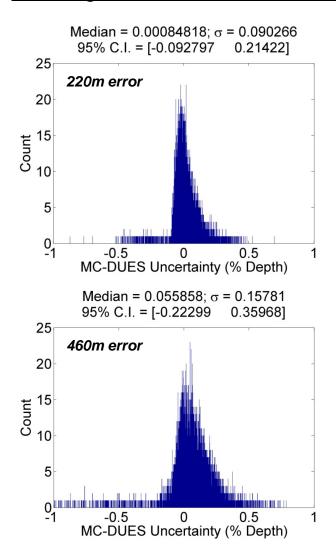
Training Area 4 – Hawaiian Islands (altimetry only)



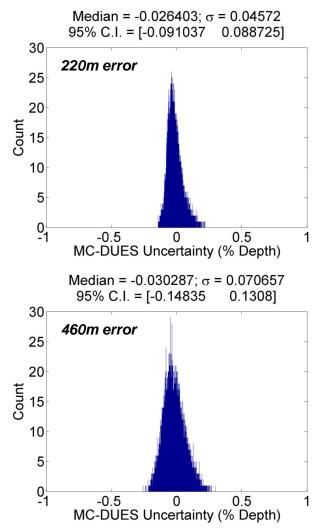
Small red box – training for 10-460 meter errors Large pink box – training for 7000 meter errors

Ensemble CPT Results

<u>Training Area 1 – Mariana Trench</u>



<u>Training Area 2 – Atlantic Slope</u>



Tabulated Differences

Differences as % depth between Monte Carlo and DUES estimators

	self			ensemble		
Horizontal Error	median	st. dev.	95th C.I.	median	st. dev.	95th C.I.

1. Mariana Trench

10m	0.04 <u>+</u> 0.04	-0.01	0.03	[068, .046]	0.02	0.03	[02, .09]
220m	0.09 <u>+</u> 0.1	-0.02	0.08	[18, .15]	< 0.01	0.09	[09, .21]
460m	0.2 <u>+</u> 0.2	-0.06	0.12	[35, .16]	0.06	0.2	[22, .36]
7 km	2 <u>+</u> 6	0.3	3.5	[-7.5, 4.5]	0.2	3.6	[-3.6, 8.3]

Worst Case σ 's

10m - 0.05%

220m - 0.2%

460m - 0.8%

7 km - 4.7%

2. Atlantic Slope

10m	0.02 <u>+</u> 0.02	-0.003	0.016	[021, .042]	-0.03	0.02	[07, .01]
220m	0.09 <u>+</u> 0.05	-0.03	0.05	[-0.09, 0.09]	-0.09	0.07	[24, .03]
460m	0.17 <u>+</u> 0.07	-0.03	0.07	[-0.15, 0.13]	-0.2	0.09	[30, .03]
7 km	0.2 <u>+</u> 6.7	-0.01	3.7	[-1.2, 1.2]	-0.1	3.6	[-1.0, 1.4]

3. Atlantic Basin

10m	0.02 <u>+</u> 0.08	>-0.01	0.05	[-0.13, 0.04]	0.01	0.05	[10, .06]
220m	0.1 <u>+</u> 1.0	-0.01	0.4	[-0.50, 0.77]	0.01	0.4	[2, 1.0]
460m	0.2 <u>+</u> 1.8	-0.03	0.8	[-1.4, 1.2]	< 0.01	0.7	[7, 1.7]
7 km	0.4 <u>+</u> 8.0	-0.1	4.7	[-8.7, 4.2]	0.1	4.7	[-8.6, 4.4]

4. Hawaii - Altimetry only

7 km	0.4 <u>+</u> 3.8	-0.1	2.2	[-3.3, 2.6]	-0.1	2.5	[-5.6, 1.5]

Questions?

Summary

Produced a computationally efficient method for estimating bathymetric uncertainty for DBDB-V

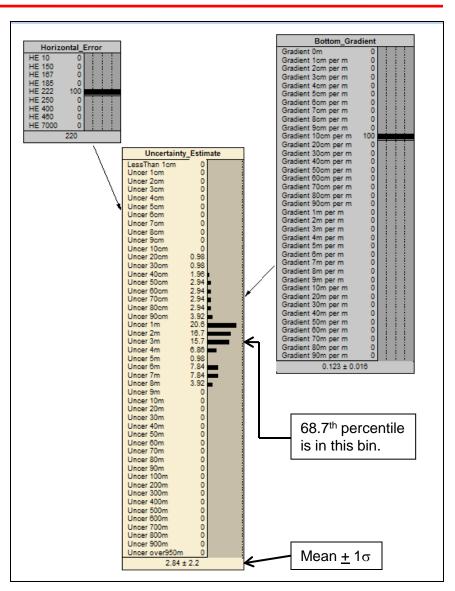
Approach

- Adapted Monte Carlo (MC) technique to Bayesian network (BN)
 - BN implementation is an extension of the Monte Carlo technique of Jakobsson et al.
- Designed & trained network using MC approach
 - BN was then interfaced inside a larger automated system to estimate uncertainty
- Examined differences between MC & BN est.
 - Differences were at worst ~8/10th of one percent of water depth when soundings data were used

Conclusion

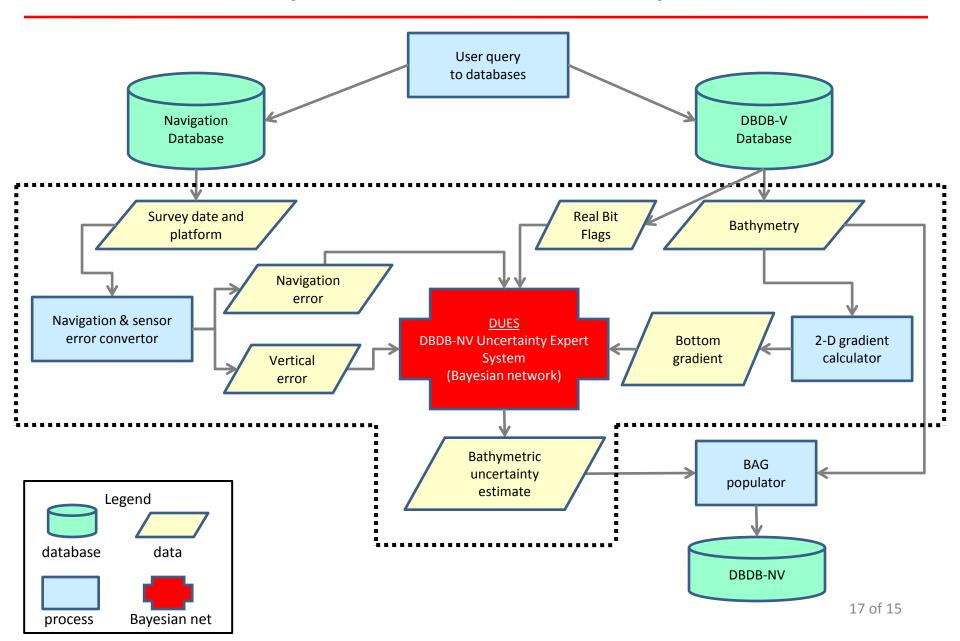
BN approach appears preliminarily to be a valid approach to bathymetric uncertainty estimation.

 Further validation required for flatter areas and with more data sets.

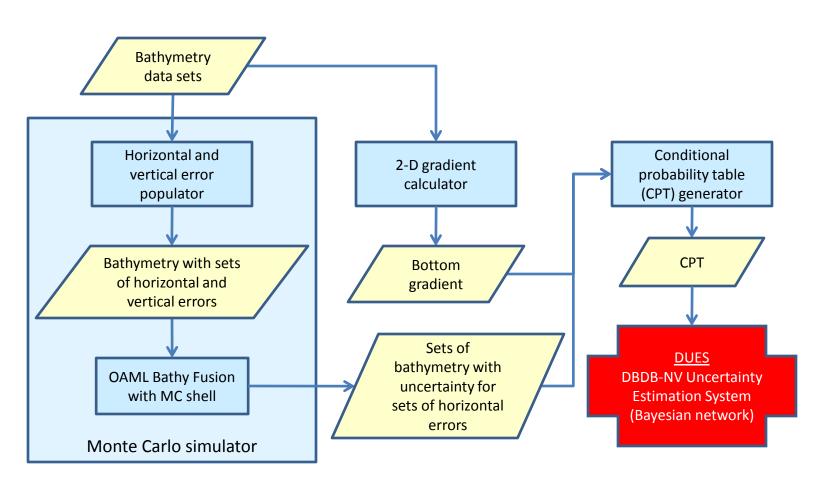


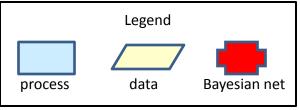
Extra Slides

Operational Concept

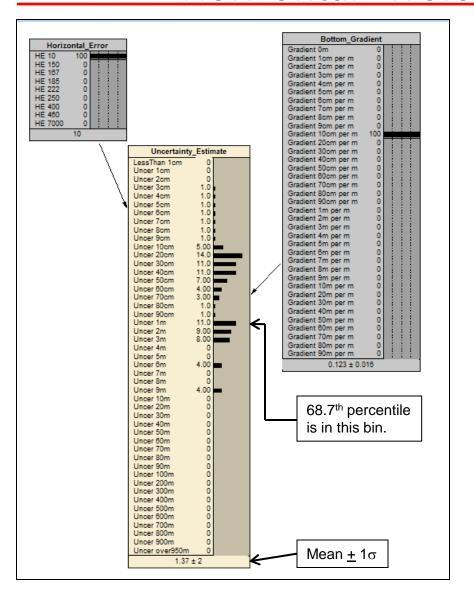


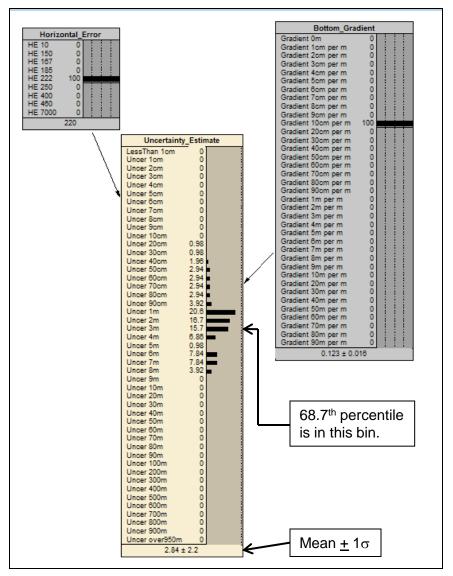
DUES Algorithm training



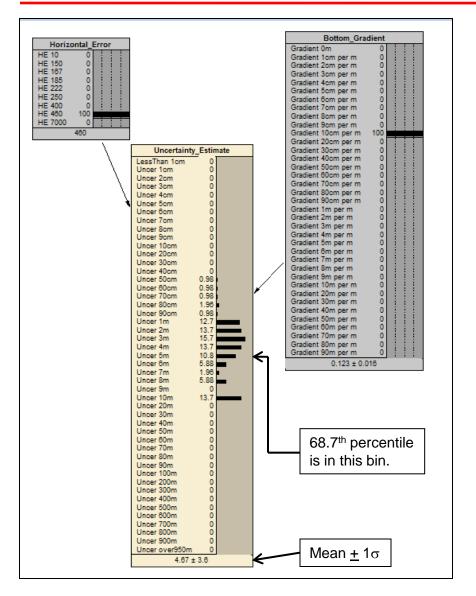


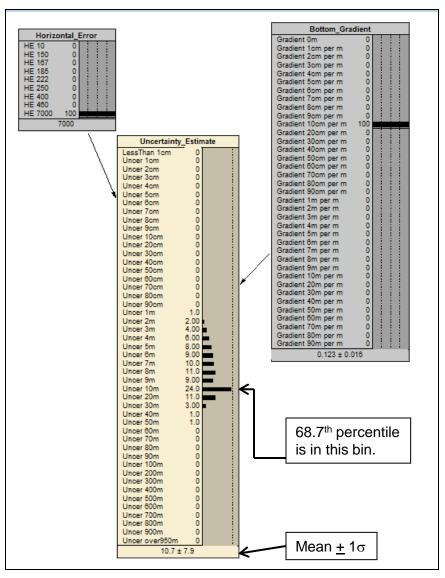
Gradient = 0.1 m/m Horizontal Errors = 10 m & 220 m



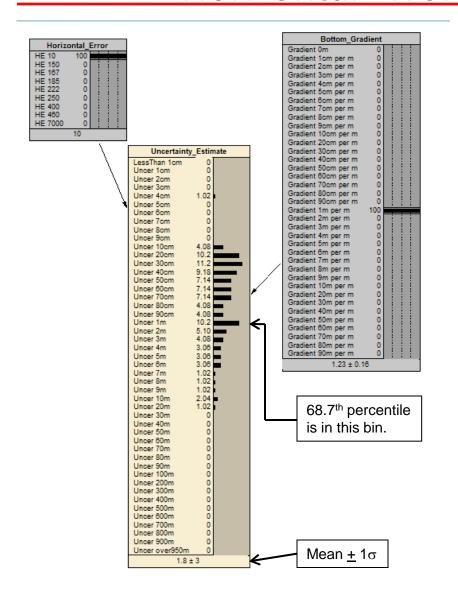


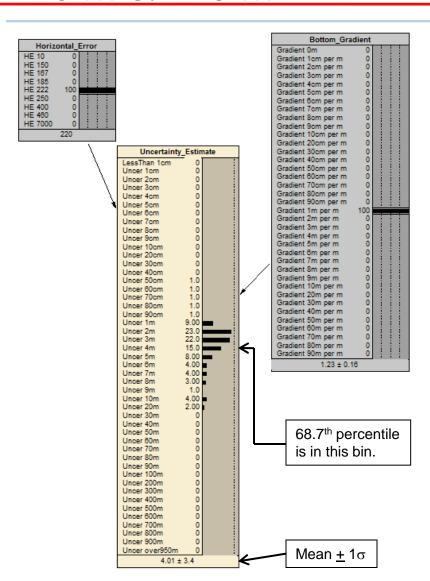
Gradient = 0.1 m/m Horizontal Errors = 460 m & 7000 m



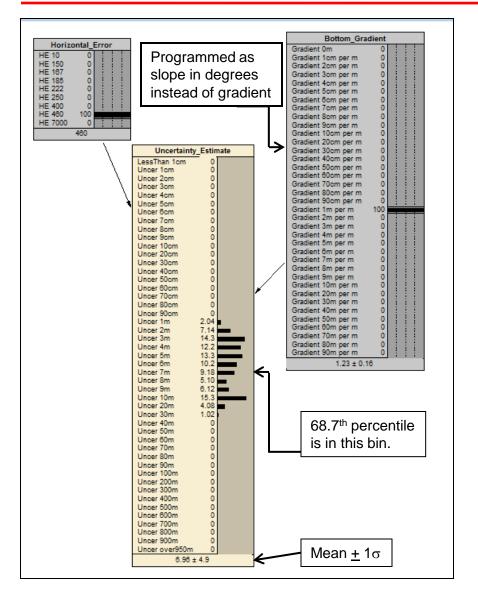


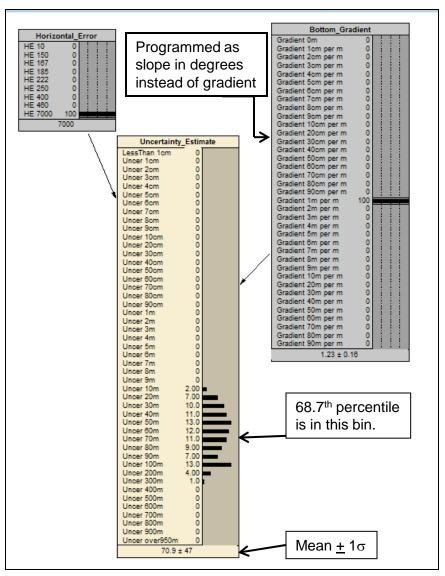
Gradient = 1.0 m/m Horizontal Errors = 10 m & 220 m



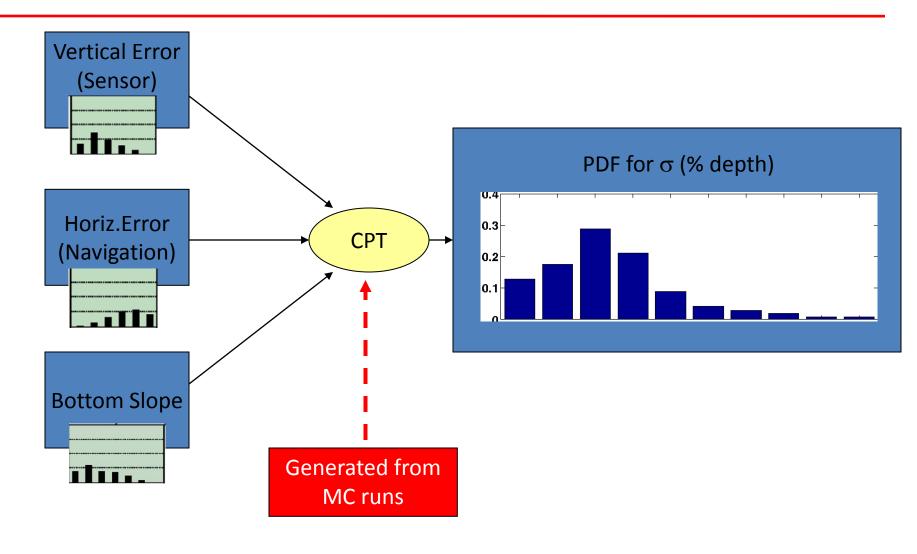


Gradient = 1.0 m/m Horizontal Errors = 460 m & 7000 m



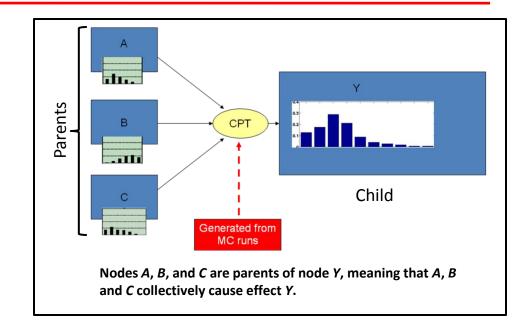


Bayesian Net Adaptation



Bayesian Network Overview

- **BN Strategy**: Exploit the similarity of how these errors propagate
 - Use BN to estimate errors for other data with similar systems and bottom slopes
- BN reduces input data and computation requirements
 - Uses probabilistic estimates and rules of statistics for computations.
 - Conditional probabilities link parent nodes (A, B, C, etc.) to child node Y
 - Conditional probability tables (CPT's) store conditional probabilities
 - Parent nodes are histograms of their variables
 - Child histogram is a weighted sum of the conditional probabilities.



• A, B, C only have one bin populated

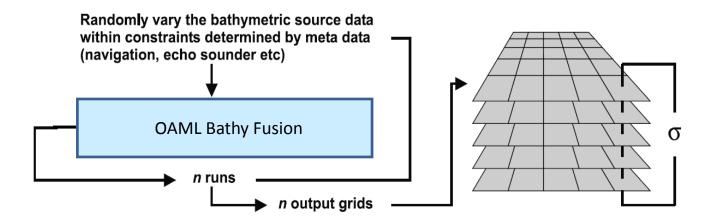
$$P(Y = y) = P(Y = y | A = a, B = b, C = c)$$

• A, B, C only have multiple bins populated

$$P(Y = y_i) = \sum_{j} \sum_{k} \sum_{l} \{ P(Y = y_i | A = a_j, B = b_k, C = c_l)$$

$$\times P(A = a_j) P(B = b_k) P(C = c_l) \}$$

Monte Carlo Training



(Adapted from Jakobbson et al. (2002) JGR, VolB12, art2358)

Uncertainty assessed from Monte Carlo simulations

- 1. Perturb sounding positions "n" times
 - Gaussian distribution of perturbed positions
 - ullet Horizontal/navigation positioning error = 1σ of Gaussian perturbation
- 2. Obtain standard deviation of the "n" bathymetry layers
- 3. Change horizontal error to next navigation error and repeat 1 & 2
- Create CPT of standard deviations with horizontal error and slope using bivariate histogram at end of simulations.