Bayesian tsunami fragility modeling considering input data uncertainty

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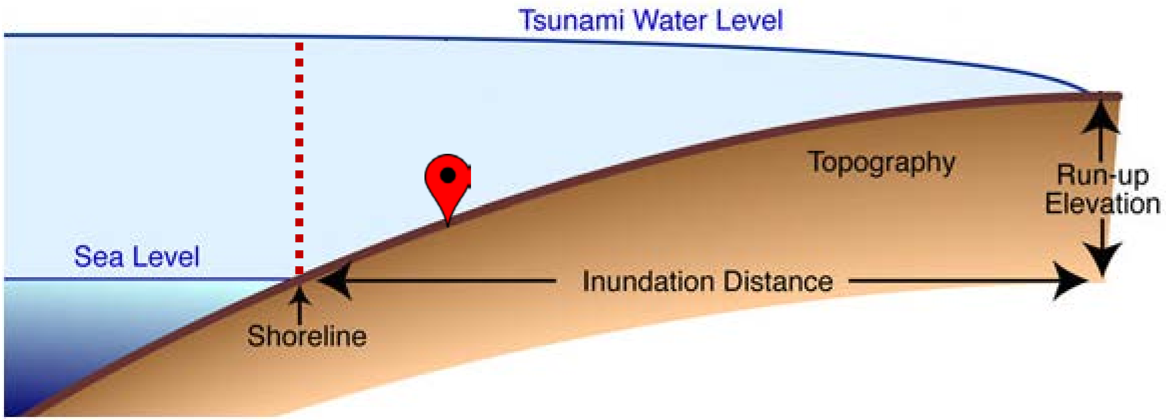
Motivation

- Empirical Tsunami Fragility modelling requires numerous pairs of Tsunami Damage Observations and Explanatory Variable related to both Hazard and Exposure.
- Tsunami Inundation Depth is the typical intensity measure adopted in developing empirical fragility.



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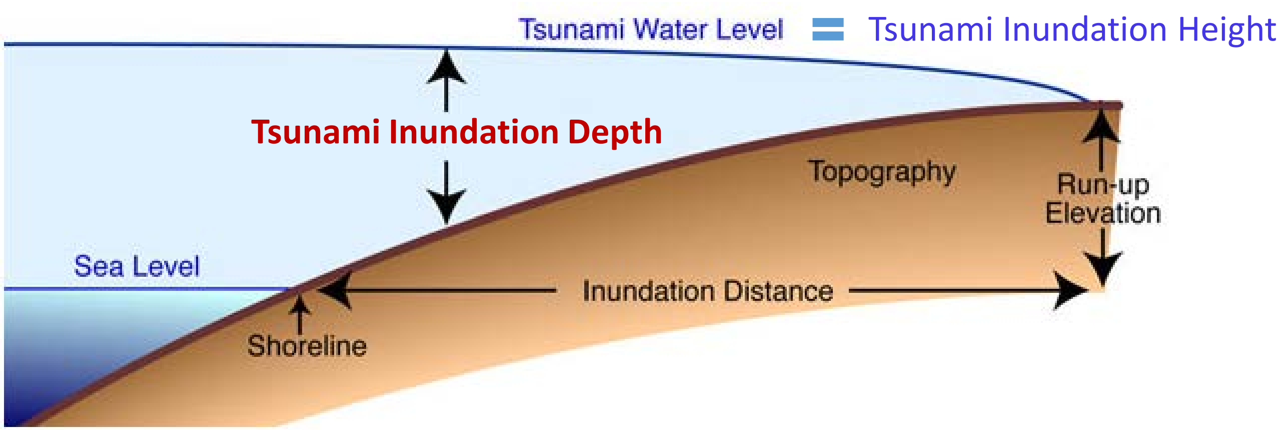

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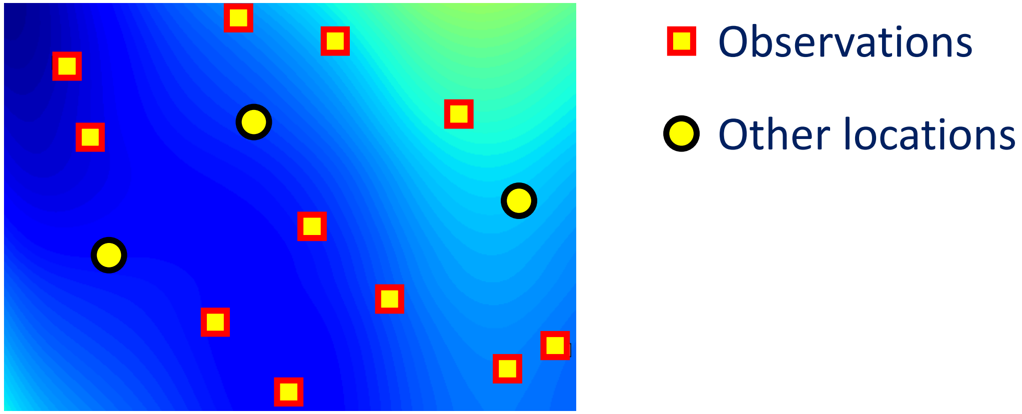
- Tsunami Inundation Depth are subject to errors due to: survey (i) techniques, (ii) equipment, and (iii) conditions.
- A further source of potential error is the operation of Interpolation when direct measurement are not available.



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Uncertainty associated with input hazard data can result in potential **overestimation of model uncertainty** associated with developed Fragilities

- In Tsunami fragility modelling, incorporation of input data errors and uncertainty has not been explored rigorously.

Scientific Questions

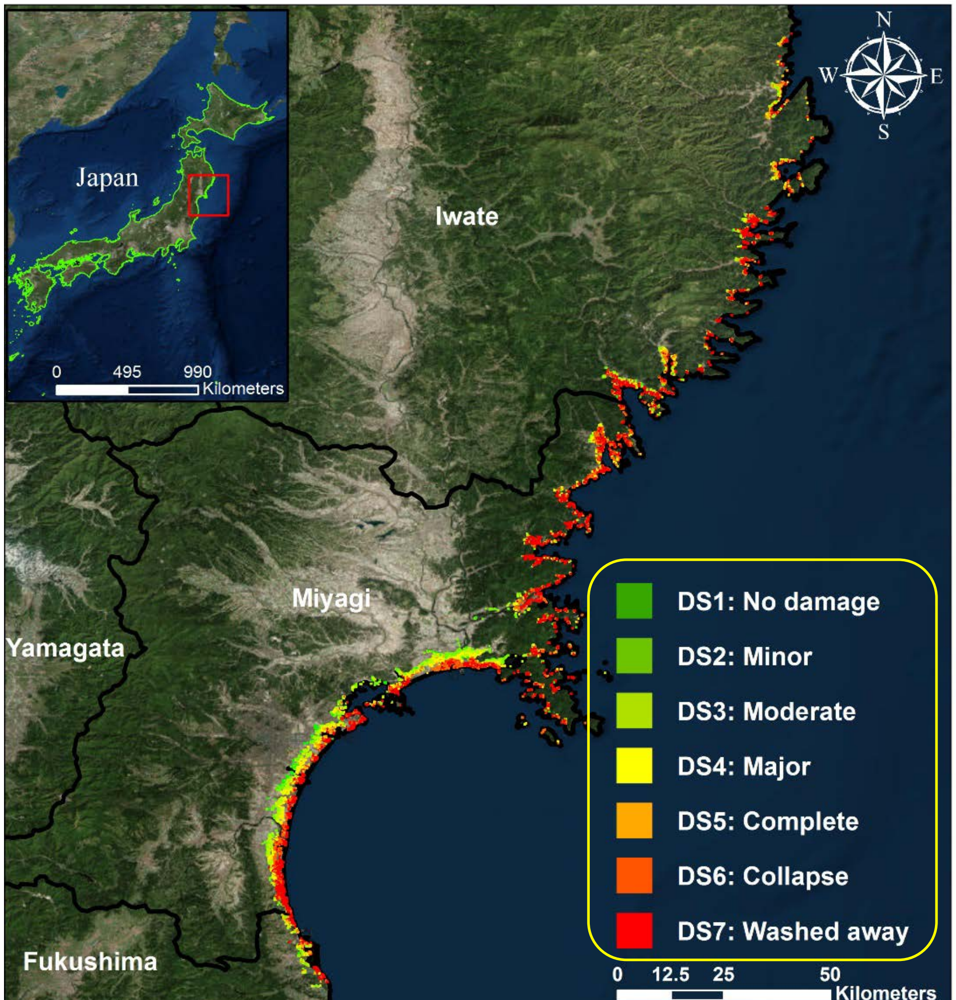
- (1) How to quantify the Uncertainty of input hazard parameters ?
- (2) How to propagate such Uncertainty on tsunami fragility function?

To respond these questions, we studied the M_W9 2011 TOHOKU event, for which a large amount of data is available

Uncertainty Quantification

First Available Database: MLIT database

MLIT (Ministry of Land, Infrastructure, and Transportation of Japanese Government)



	Description	Condition
2	There is no significant structural or non-structural damage, possibly only minor flooding	Possible to be use immediately after minor floor and wall clean up
3	Slight damages to non-structural components	Possible to be use after moderate reparation
4	Heavy damages to some walls but no damages in columns	Possible to be use after major reparations
5	Heavy damages to several walls and some columns	Possible to be use after a complete reparation and retrofitting
6	Destructive damage to walls (more than half of wall density) and several columns (bend or destroyed)	Loss of functionality (system collapse). Non-repairable or great cost for retrofitting
7	Washed away, only foundation remained, total overturned	Non-repairable, requires total reconstruction

Non Structural: 1 2 3

Structural: 4 5 6 7

∀ **Observation**: Location, **h**, Material, Damage State, Number of stories, etc.

Uncertainty Quantification

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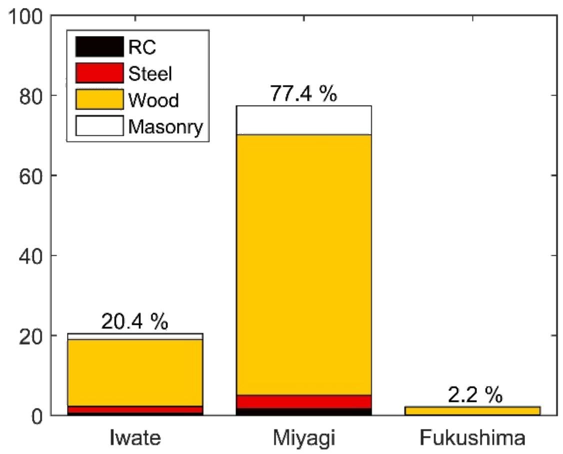
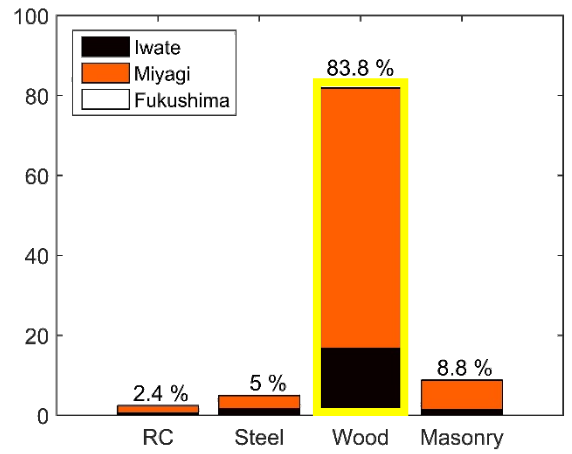
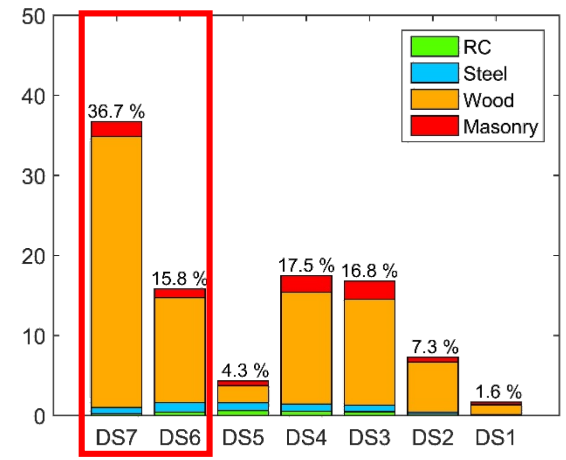
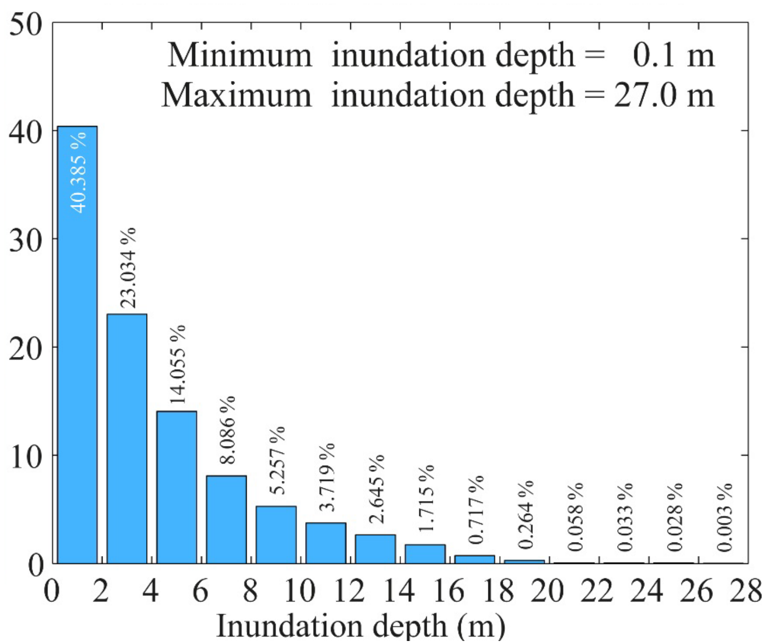
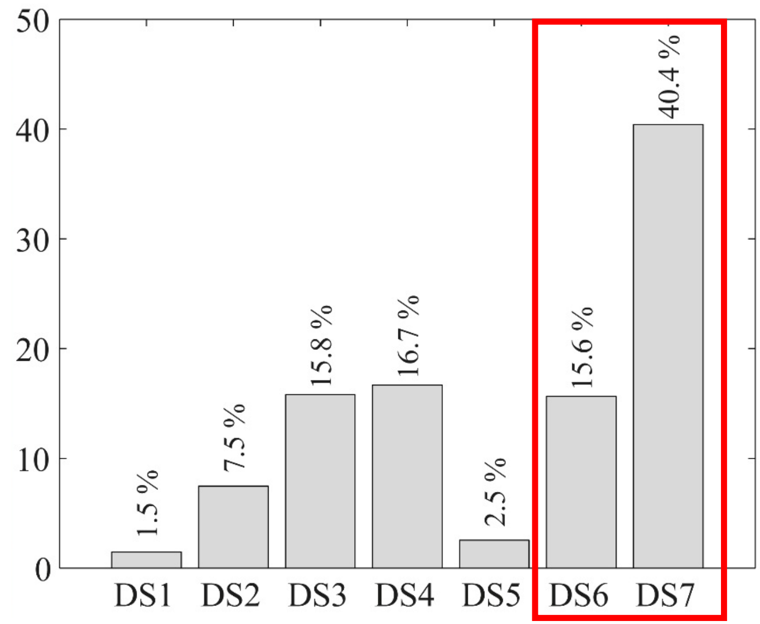










MLIT database Accuracy

Two sources of uncertainty associated to the Intensity Measures:

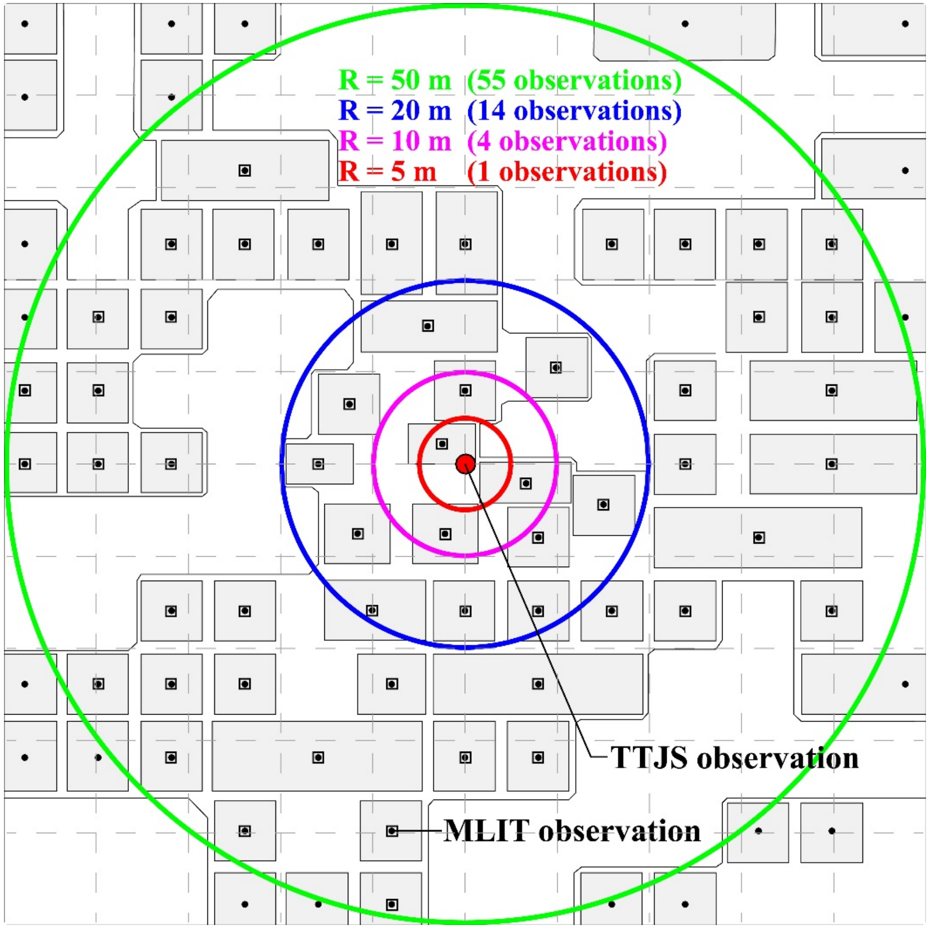
1. Error due to interpolation/smoothing: recordings are based on MLIT 100-m data;
2. Elevation data at each building sites are not available; therefore there is not a straightforward correlation between tsunami height and tsunami depth.

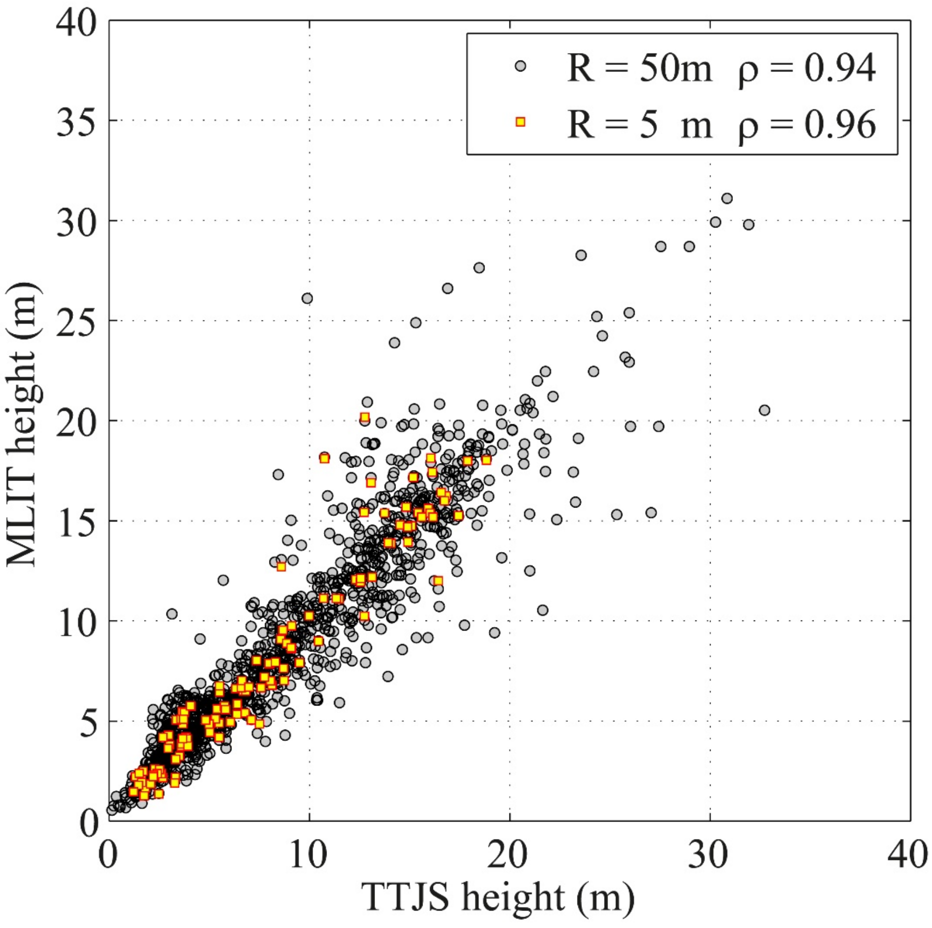
It is not straightforward to estimate the MLIT data accuracy

Second Available Database: TTJS database (Tohoku Tsunami Joint Survey)

1. More reliable than MLIT database (vertical accuracy within few centimeters, as DEM the GSI data are used) but less populated;
2. Heights of watermarks on buildings, trees, and walls were measured using a laser range finder, a level survey, a real-time kinematic global positioning system (RTK-GPS) receiver with a cellular transmitter, and total stations.

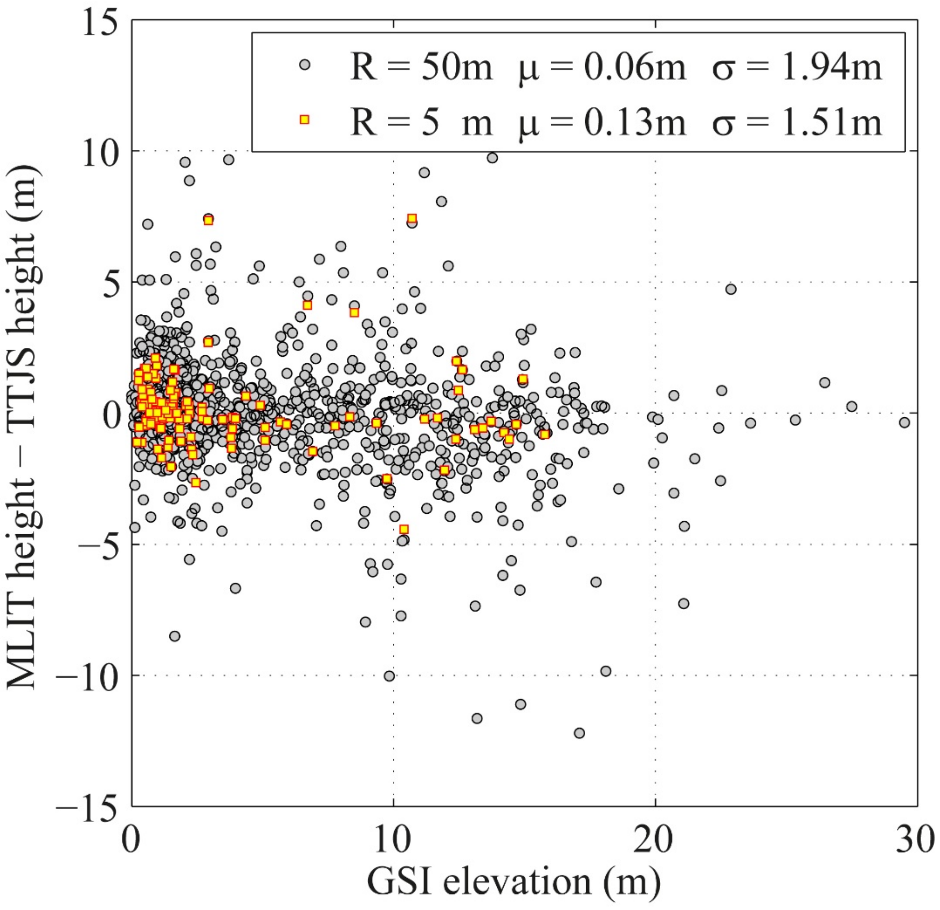
Procedure for Uncertainty Quantification



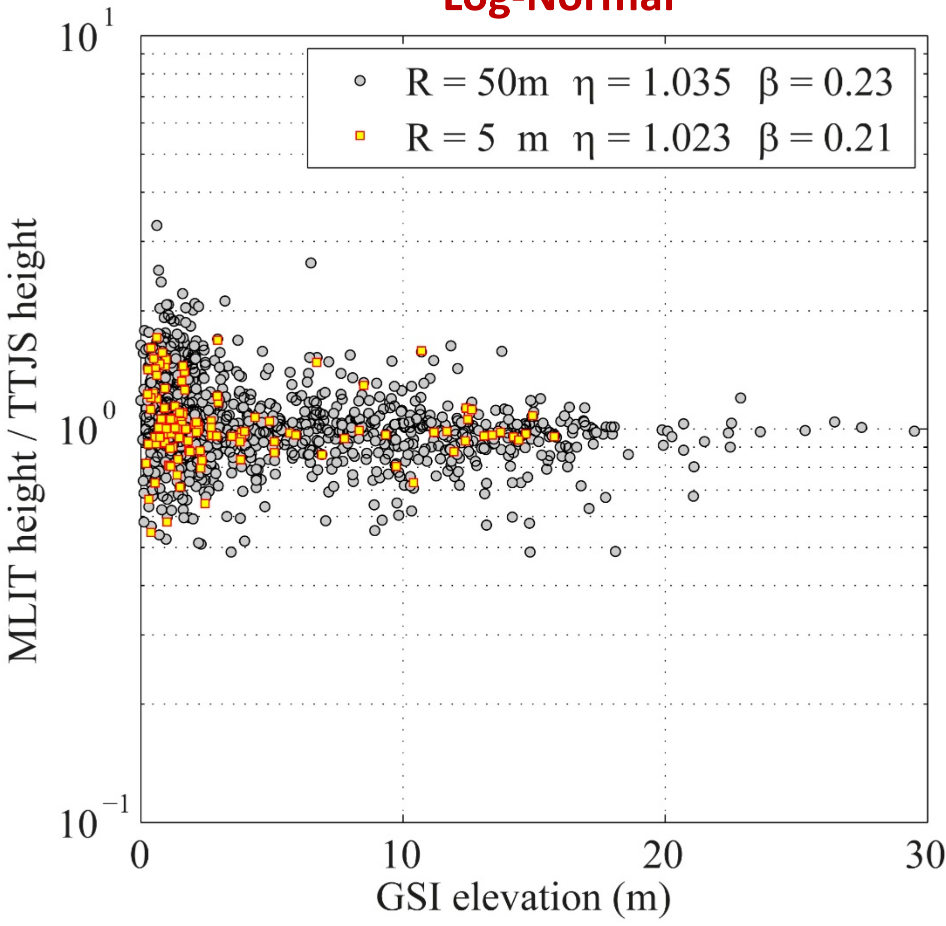


Procedure for Uncertainty Quantification

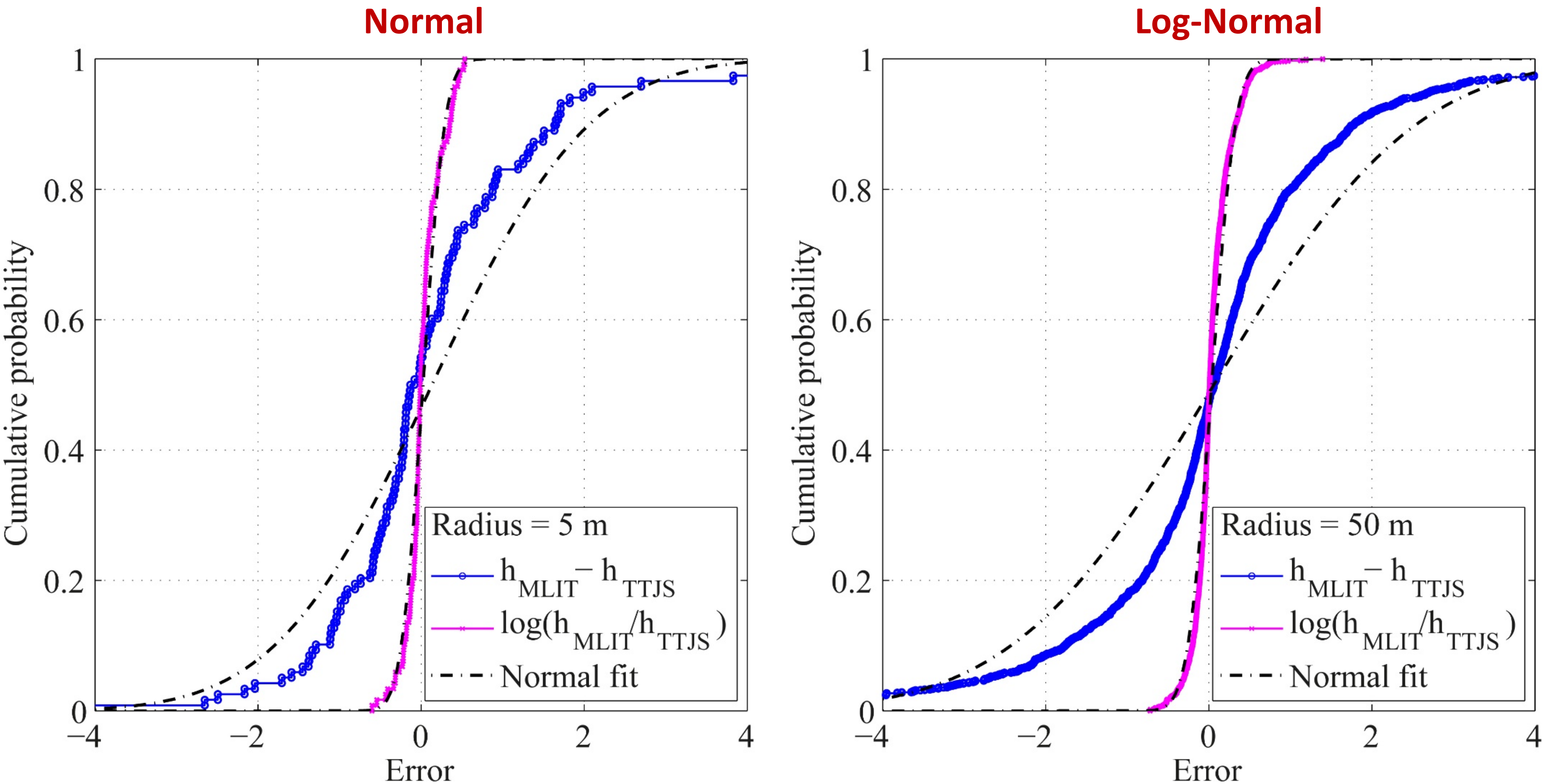
Normal



Log-Normal



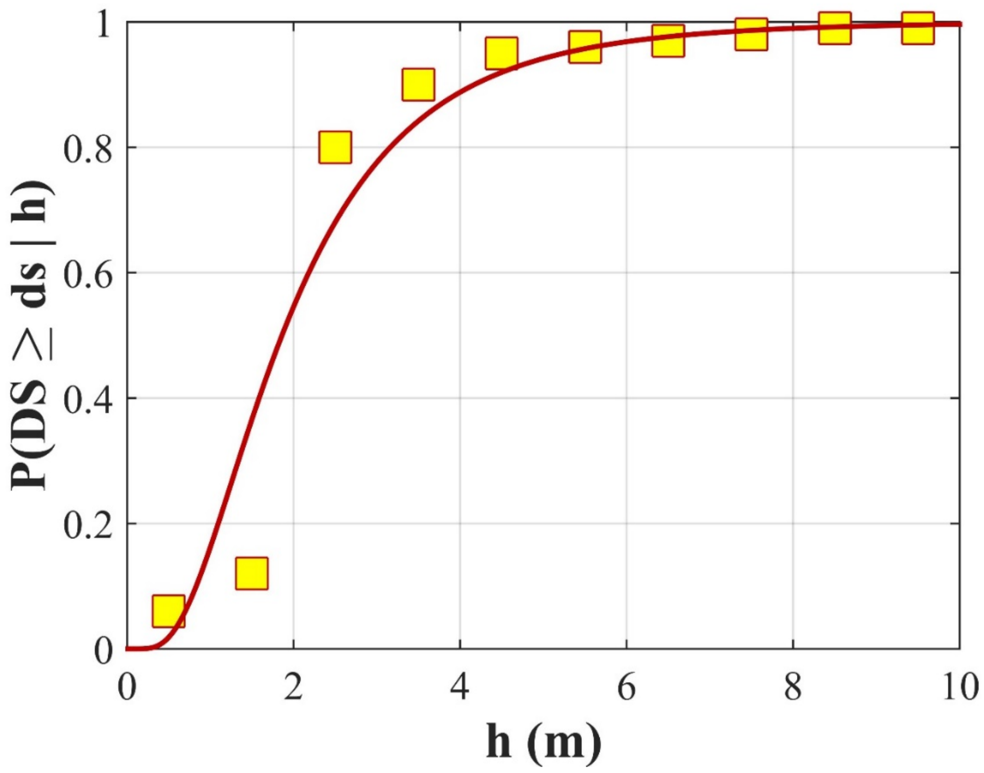
Procedure for Uncertainty Quantification



Lognormal, η equal to 1 and logarithmic standard deviation equal to 0.25

First Step: Typical Tsunami Empirical Fragility models

(1) Log-Normal Method



- **Binning**
- **Change of variables**
- **Linear fitting**

$$\ln h = \ln \eta + \beta \cdot \Phi^{-1}\left[P\left(DS \geq ds \mid h\right)\right] + \varepsilon_R$$

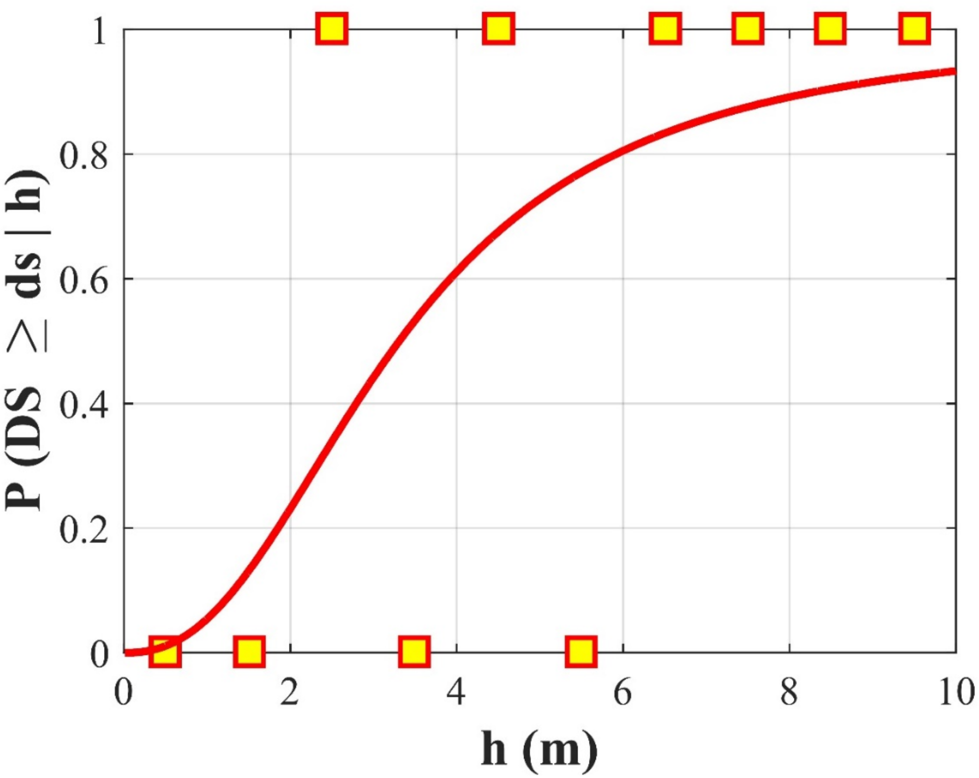
- **Change of variables**

$$P\left(DS \geq ds \mid h\right) = \Phi\left(\frac{\ln h - \ln \eta}{\beta}\right)$$

Two Parameters for each damage state: η and β

First Step: Typical Tsunami Empirical Fragility models

(2) Binomial Logistic Method



- **Probability of occurrence**

$$\prod_{i=1}^{n}\binom{1}{y_i}\cdot\pi_i^{y_i}\cdot(1-\pi_i)^{1-y_i}$$

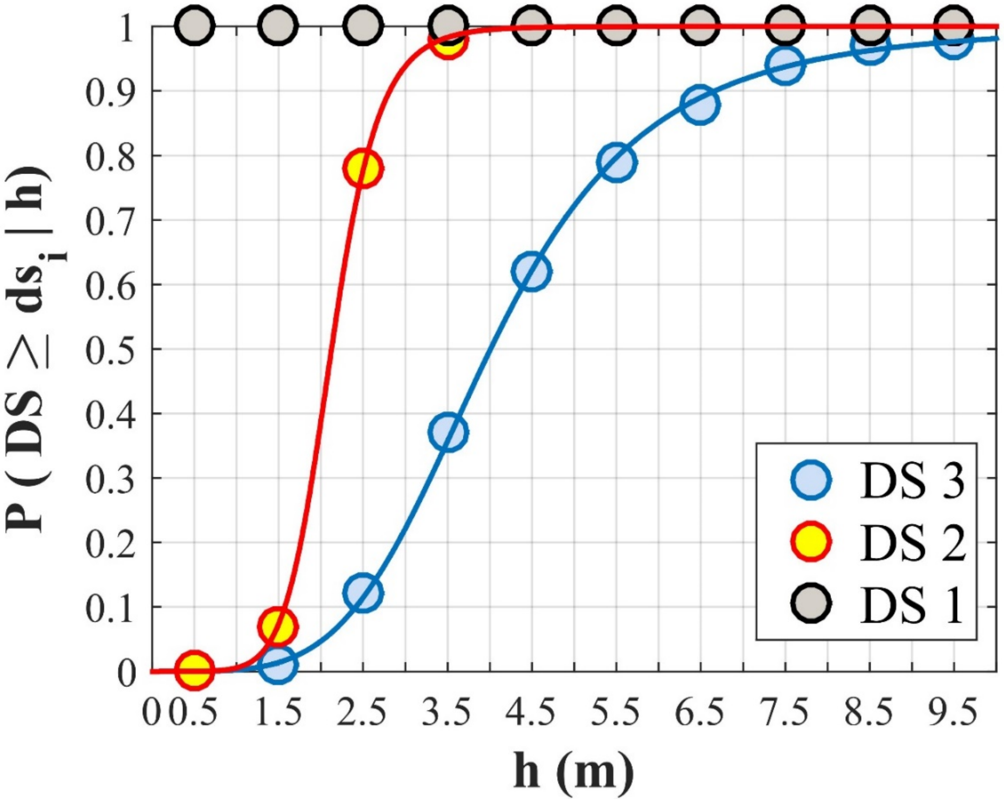
- **π_i may assume different forms**
- Logit

$$\pi_i=\frac{\exp(b_1+b_2\cdot\ln h_i)}{1+\exp(b_1+b_2\cdot\ln h_i)}$$

Two Parameters for each damage state: b_1 and b_2

First Step: Typical Tsunami Empirical Fragility models

(3) Multinomial Logistic Method



- **Binning**
- **Probability of occurrence**

$$\frac{m_i\,!}{\prod_{j=1}^{k} y_{ij}\,!}\prod_{j=1}^{k}\pi_{ij}^{y_{ij}}$$

- **π_i may assume different forms**

$$\pi_{ij}=\frac{\exp\left(b_{1,j}+b_{2,j}\cdot\ln h_i\right)}{1+\exp\left(b_{1,j}+b_{2,j}\cdot\ln h_i\right)}\cdot\left(1-\sum_{l=1}^{j-1}\pi_{il}\right)$$

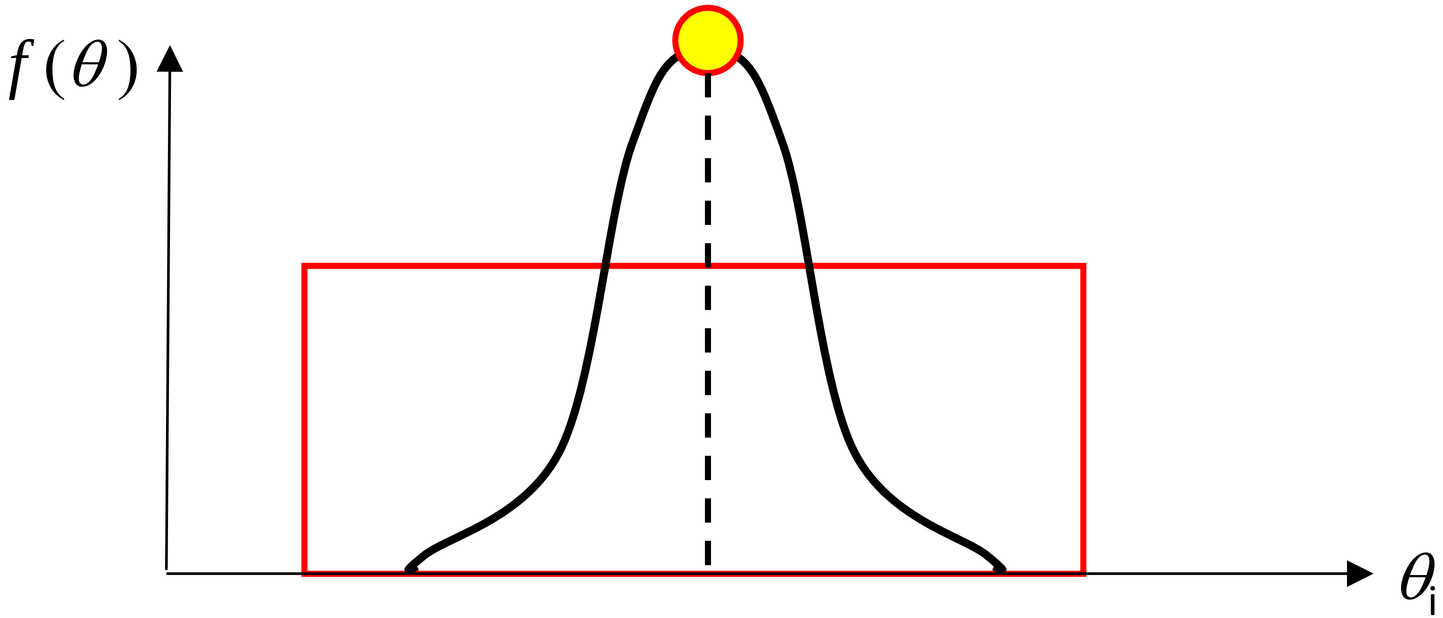
Two Parameters for each damage state: b_{1i} and b_{2i}

Second Step: **Bayesian procedure**

$$f(\boldsymbol{\theta}|\mathbf{D}) = c^{-1} \cdot L(\mathbf{D}|\boldsymbol{\theta}) \cdot f(\boldsymbol{\theta}) \qquad c = \int L(\mathbf{D}|\boldsymbol{\theta}) \cdot f(\boldsymbol{\theta}) \cdot d\boldsymbol{\theta} \qquad L(\mathbf{D}|\boldsymbol{\theta}) = \prod_{i=1}^{n} f(\boldsymbol{D}_i|\boldsymbol{\theta})$$

The likelihood function depend by the adopted typology of regression.

The parameters maximizing the posteriors represent the solution of the Bayesian regression (i.e. the Bayesian maximum likelihood).



Uncertainty Propagation

Second Step: Bayesian procedure

$$f(\boldsymbol{\theta}|\mathbf{D}) = c^{-1} \cdot L(\mathbf{D}|\boldsymbol{\theta}) \cdot f(\boldsymbol{\theta}) \qquad c = \int L(\mathbf{D}|\boldsymbol{\theta}) \cdot f(\boldsymbol{\theta}) \cdot d\boldsymbol{\theta} \qquad L(\mathbf{D}|\boldsymbol{\theta}) = \prod_{i=1}^{n} f(\boldsymbol{D_i}|\boldsymbol{\theta})$$

The likelihood function depend by the adopted typology of regression.

The parameters maximizing the posteriors represent the solution of the Bayesian regression (i.e. the Bayesian maximum likelihood).

How to implement the uncertainty on the intensity measure?

$$f(\boldsymbol{D_i}|\boldsymbol{\theta}) = \int_{-\infty}^{+\infty} f(\boldsymbol{D_i}|\varepsilon, \boldsymbol{\theta}) \cdot f_i(\varepsilon) \cdot d\varepsilon$$

$$L(\mathbf{D}|\boldsymbol{\theta}) = \prod_{i=1}^{n} \int_{-\infty}^{+\infty} f(\boldsymbol{D_i}|\varepsilon, \boldsymbol{\theta}) \cdot f_i(\varepsilon) \cdot d\varepsilon$$

Uncertainty Propagation

Second Step: Bayesian procedure

(1) Log-Normal Method

$$\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}\cdot\sigma_R}\cdot\exp\left\{-\frac{1}{2\cdot\sigma_R^2}\cdot\left[\ln h_i+\varepsilon_{\ln h}-\ln\eta-\beta\cdot\Phi^{-1}\left(P\left(DS\geq ds\,|\,h_i\right)\right)\right]^2\right\}\cdot f\left(\varepsilon_{\ln h}\right)\cdot d\varepsilon_{\ln h}$$

(2) Binomial Logistic Method

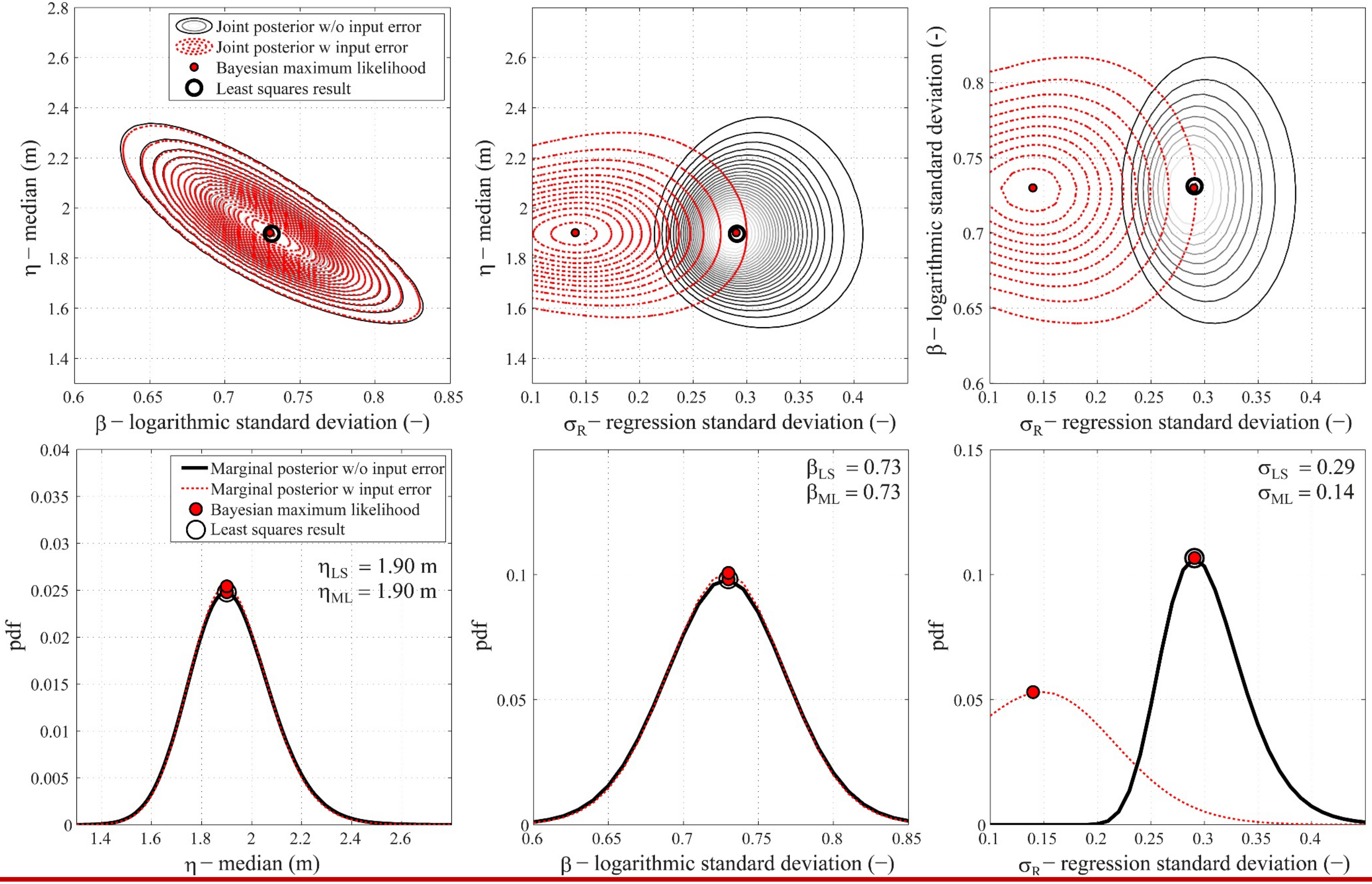
$$\int_{-\infty}^{+\infty}\binom{1}{y_i}\cdot\left[\frac{\exp\left(b_1+b_2\cdot\left(\ln h_i+\varepsilon_{\ln h}\right)\right)}{1+\exp\left(b_1+b_2\cdot\left(\ln h_i+\varepsilon_{\ln h}\right)\right)}\right]^{y_i}\cdot\left[1-\frac{\exp\left(b_1+b_2\cdot\left(\ln h_i+\varepsilon_{\ln h}\right)\right)}{1+\exp\left(b_1+b_2\cdot\left(\ln h_i+\varepsilon_{\ln h}\right)\right)}\right]^{1-y_i}\cdot f\left(\varepsilon_{\ln h}\right)\cdot d\varepsilon_{\ln h}$$

(3) Multinomial Logistic Method

$$\prod_{j=1}^{k}\int_{-\infty}^{+\infty}\frac{\exp\left(b_{1,j}+b_{2,j}\cdot\left(\ln h+\varepsilon_{\ln h}\right)\right)}{1+\exp\left(b_{1,j}+b_{2,j}\cdot\left(\ln h+\varepsilon_{\ln h}\right)\right)}\cdot\left(1-\sum_{l=1}^{j-1}\pi_{il}\right)\cdot f\left(\varepsilon_{\ln h}\right)\cdot d\varepsilon_{\ln h}$$

Uncertainty Propagation

Numerical Results: Log-Normal Method



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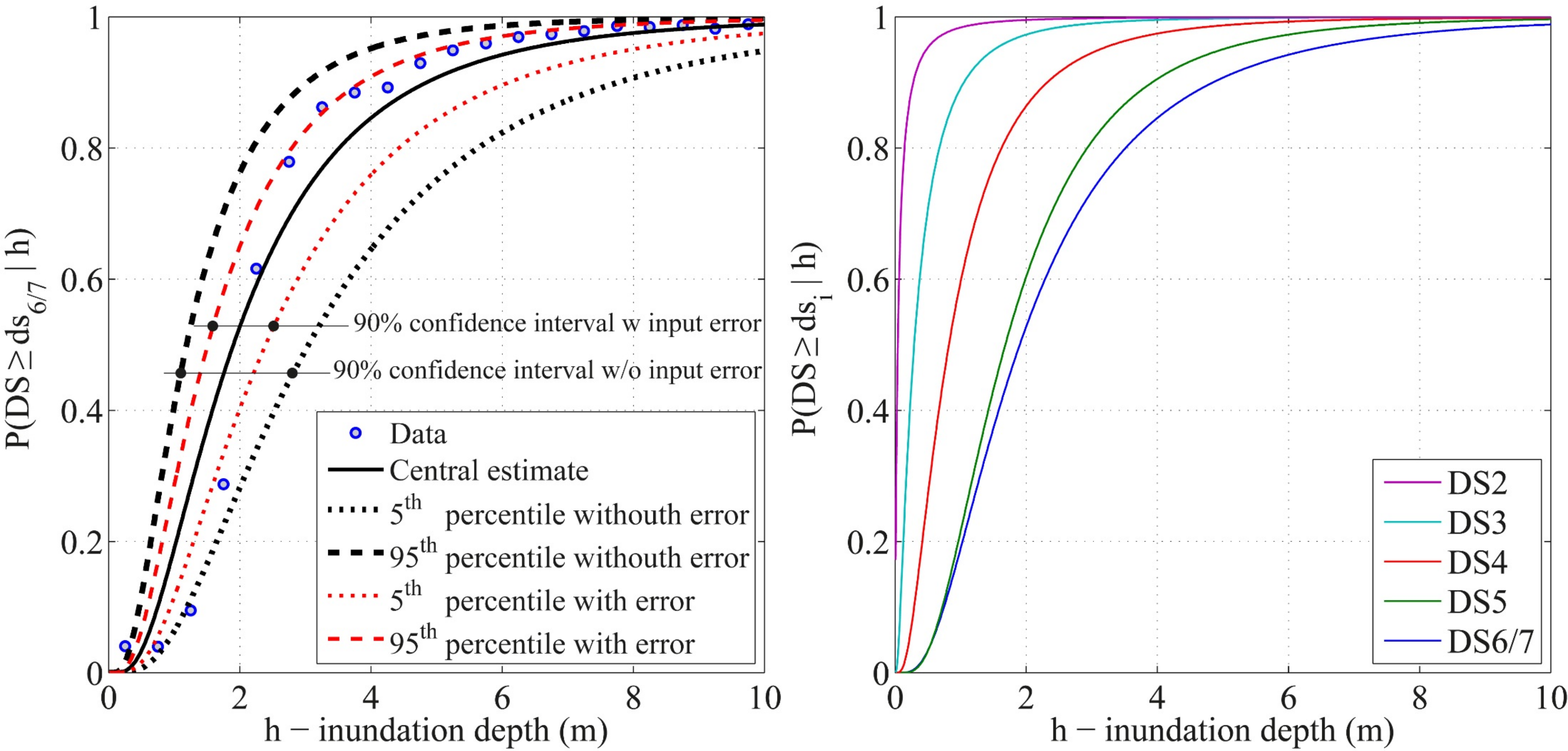
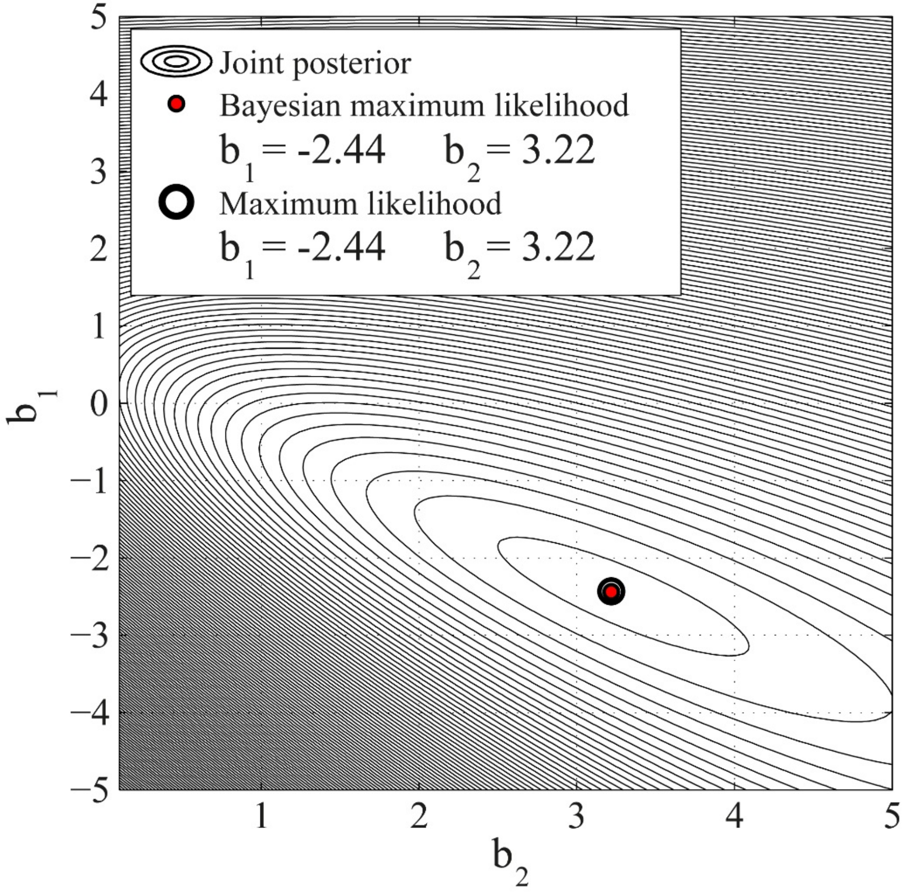
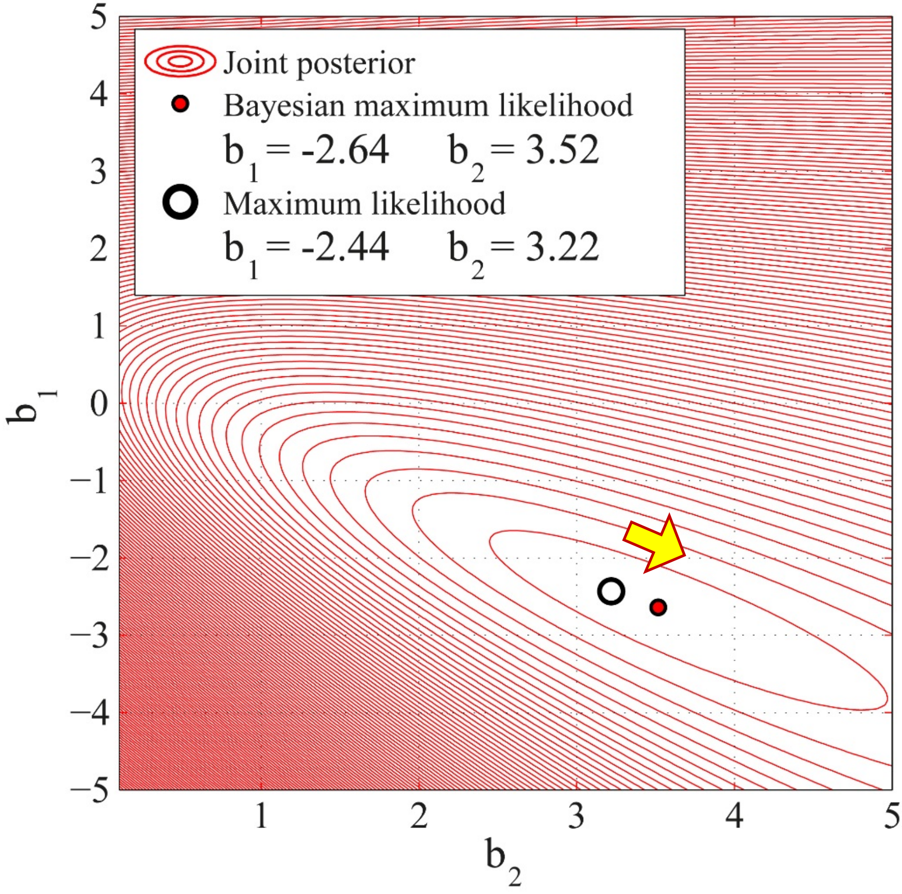


Numerical Results: Binomial Logistic Method

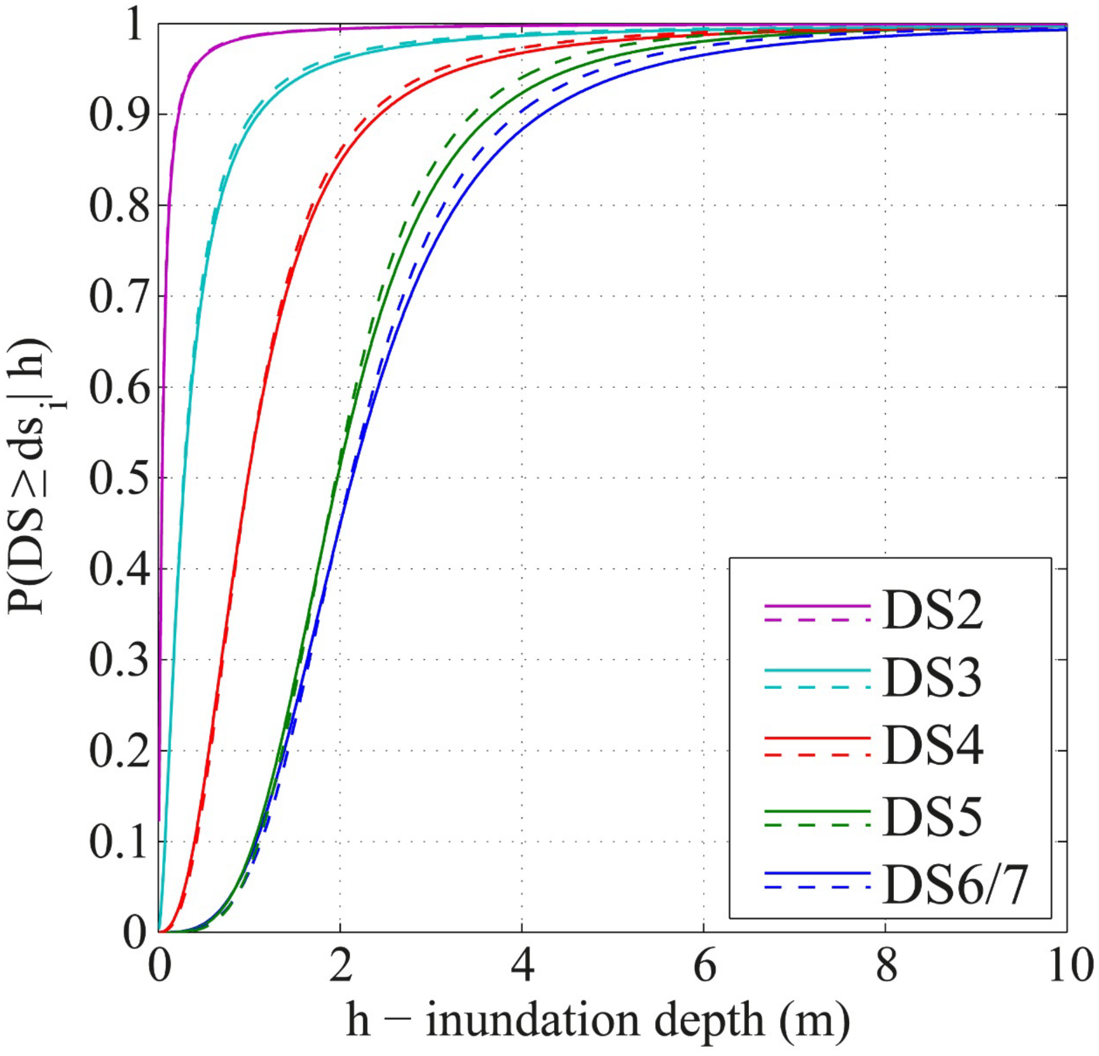
Without



With

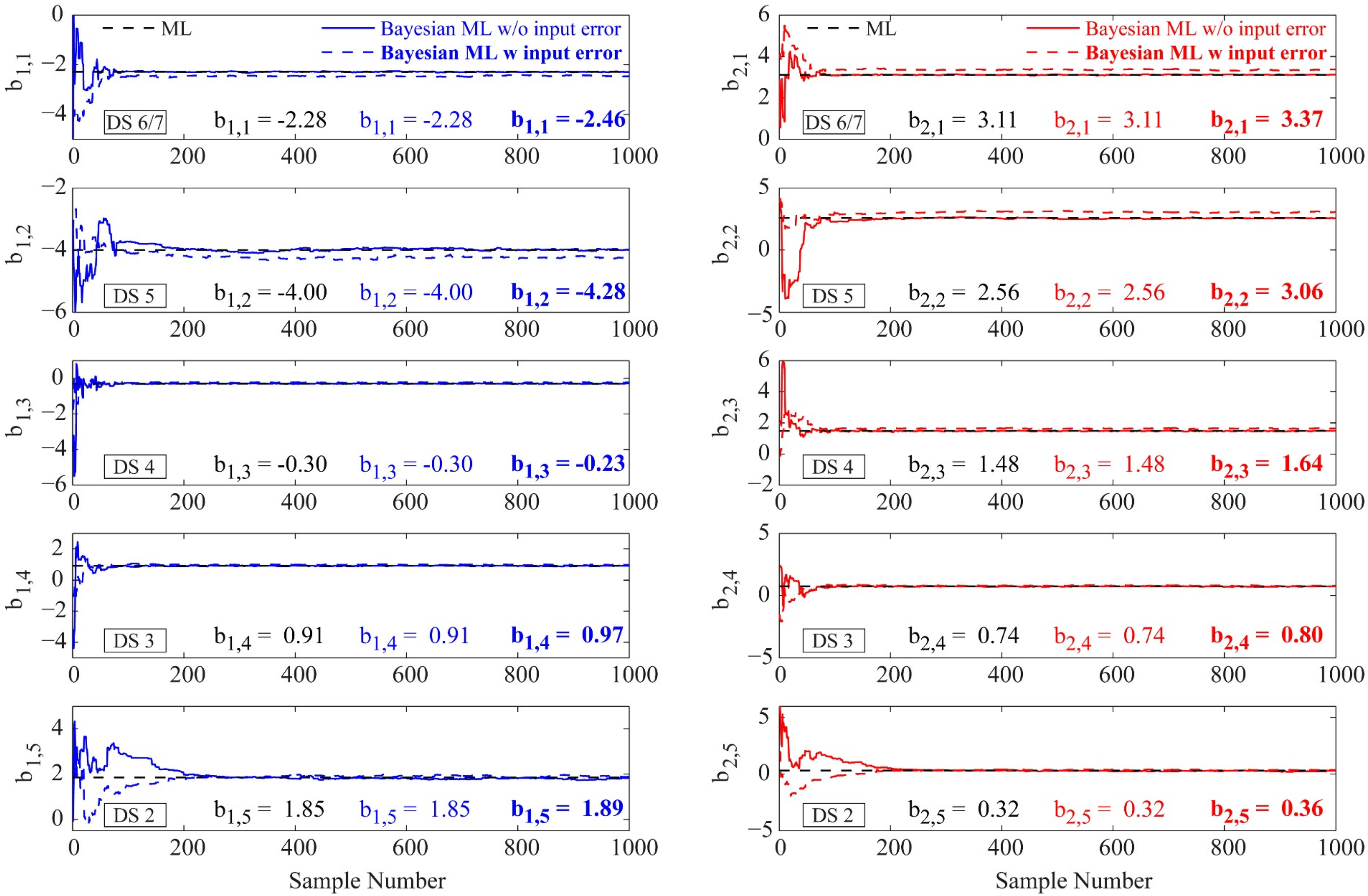


Numerical Results: Binomial Logistic Method

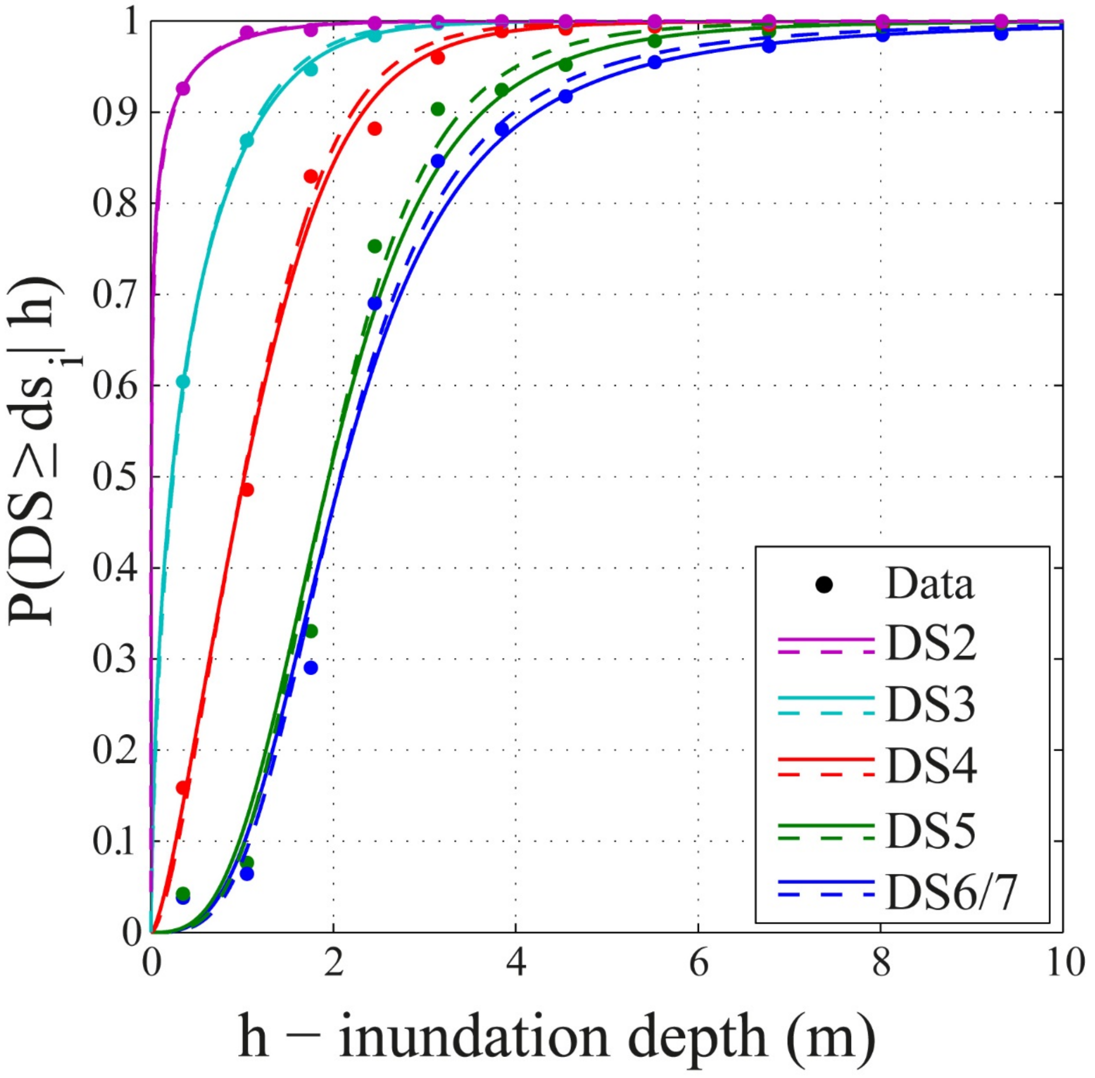


Uncertainty Propagation

Numerical Results: Multinomial Logistic Method



Numerical Results: Multinomial Logistic Method



Uncertainty Propagation

Effects on the Risk Assessment

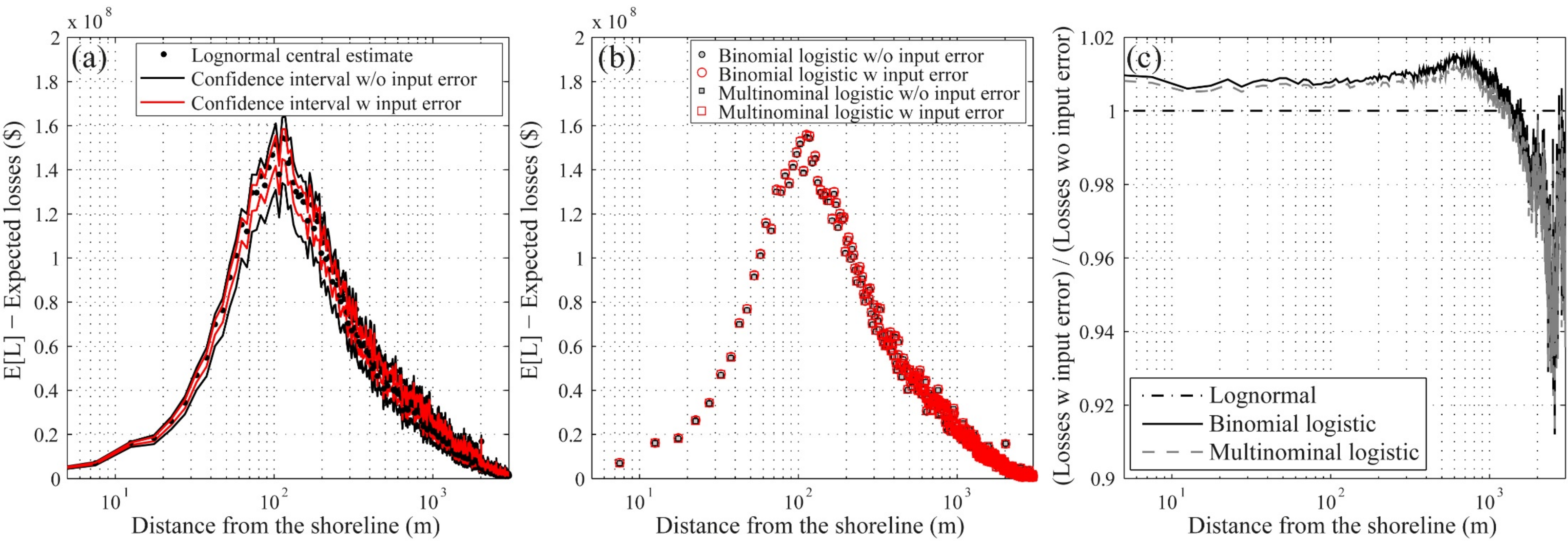
$$E[L] = \sum_{j=1}^{k} R_j \cdot \left[P\left(DS \geq ds_j\right) - P\left(DS \geq ds_{j+1}\right) \right]$$

μ_R = 1600 \$/m^2

σ_R = 32%

1	2	3	4	5	6&7
0%	5%	20%	40%	60%	100%

1000 simulations



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Future Developments

- Multivariate Empirical Tsunami Fragility, i.e. consider not only tsunami depth but also tsunami velocity.
- Identification of a methodology for the quantification of the input data uncertainty for the velocity.
- Propagate the entire distribution of the parameters for a robust regression.
- Potential extension to experimental database to remove from the capacity models the measurement error or other typologies of error that can be quantified.

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Thank you for your attention!

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