ΤΜΗΜΑ ΠΟΛΙΤΙΚΩΝ ΜΗΧΑΝΙΚΩΝ
ΜΠΣ “ΔΙΑΧΕΙΡΙΣΗ ΥΔΡΟΜΕΤΕΩΡΟΛΟΓΙΚΩΝ ΚΑΤΑΣΤΡΟΦΩΝ”

# Υδροπληροφορική και Συστήματα Υποστήριξης Αποφάσεων (DSS) για τον κίνδυνο πλημμύρας σε αστικές περιοχές

# Ανάλυση αβεβαιοτήτων- Προσομοίωση Monte Carlo


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ΔΗΜΟΚΡΙΤΕΙΟ
ΠΑΝΕΠΙΣΤΗΜΙΟ
ΘΡΑΚΗΣ

- Sensitivity - Uncertainty
- Sensitivity analysis application
- Uncertainty analysis application using monte carlo

**Sensitivity - Uncertainty**

Sensitivity analysis application

Uncertainty analysis application using monte carlo

# Sensitivity - Uncertainty

## Deterministic - Stochastic

- **Deterministic hydrology.** In deterministic hydrology one is usually aware of these errors. They are taken into account, often in a primitive way, during calibration of models. During this phase of the modelling process one tries to find the parameter values of the model (e.g. surface roughness or hydraulic conductivity) such that the magnitude of the residuals is minimized. After calibration of the model, the errors are not explicitly taken into account while performing further calculations with the model. Errors in model outcomes are thus ignored.

Bierkens & van Geer, 2012

# Sensitivity - Uncertainty

## Deterministic - Stochastic

- **Stochastic Hydrology.** Stochastic hydrology not only tries to use models for predicting hydrological variables, but also tries to quantify the errors in model outcomes. Of course, in practice we do not know the exact values of the errors of our model predictions; if we knew them, we could correct our model outcomes for them and be totally accurate. What we often do know, usually from the few measurements that we did take, is some probability distribution of the errors. Here it suffices to know that a probability distribution tells one how likely it is that an error has a certain value.

Bierkens & van Geer, 2012

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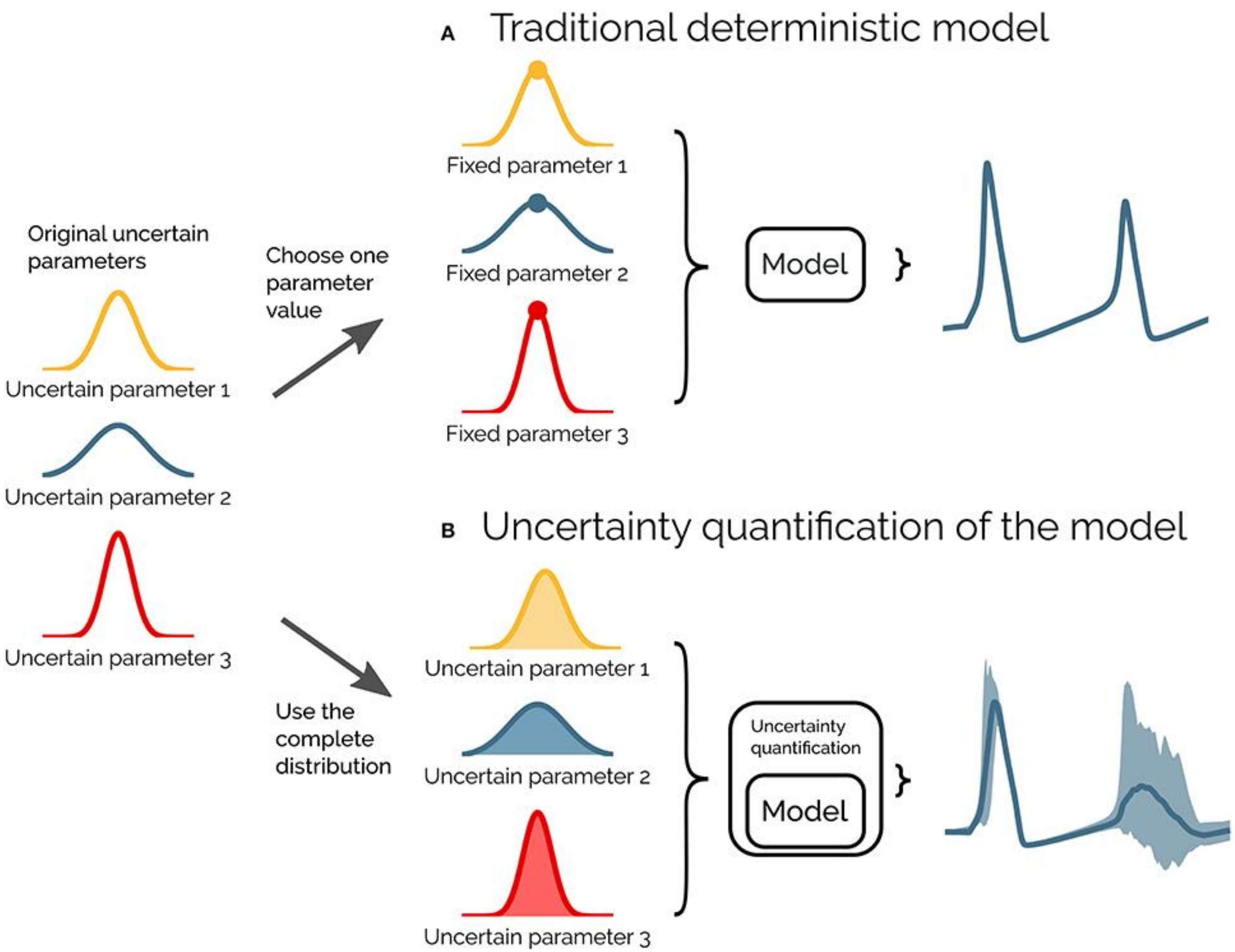
# Sensitivity - Uncertainty




Tennøe et al., 2018

# Sensitivity - Uncertainty

## Sensitivity analysis

Sensitivity analysis procedures explore and quantify the impact of possible errors in input data on predicted model outputs and system performance indices. Simple sensitivity analysis procedures can be used to illustrate either graphically or numerically the consequences of alternative assumptions about the future.

**‘Sensitivity analysis’ aims to describe how much model output values are affected by changes in model input values.**

Loucks & van Beek, 2017

# Sensitivity - Uncertainty

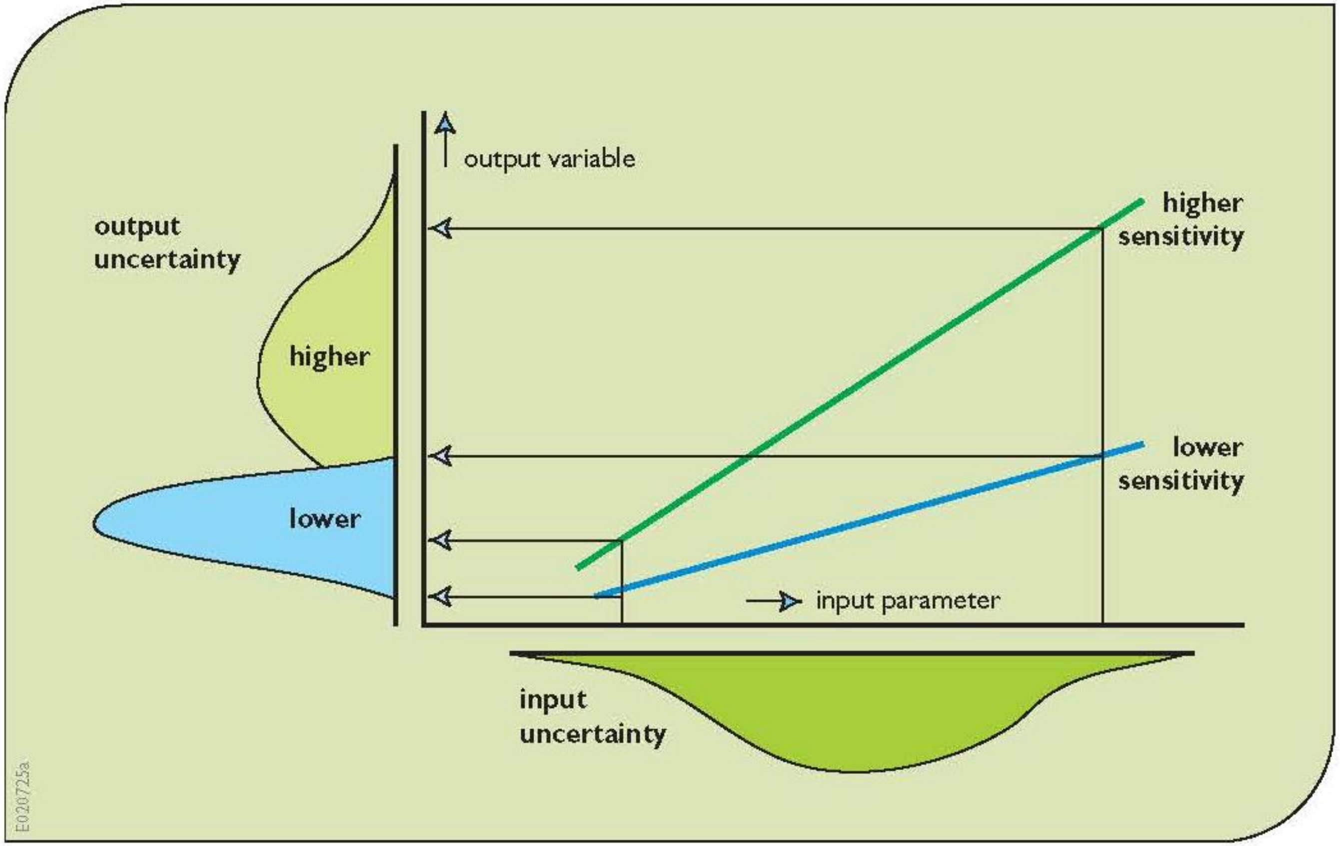
## Uncertainty analysis

Uncertainty analyses employing probabilistic descriptions of model inputs can be used to derive probability distributions of model outputs and system performance indices.

**Uncertainty involves the notion of randomness**. If a value of a performance indicator or performance measure, like the phosphorus concentration or the depth of water at a particular location, varies, and this variation over space and time cannot be predicted with certainty, it is called a random variable. One cannot say with certainty what the value of a random variable will be but only **the likelihood or probability that it will be within some specified range of values**. **The probabilities of observing particular ranges of values of a random variable are described or defined by a probability distribution.**

Loucks & van Beek, 2017

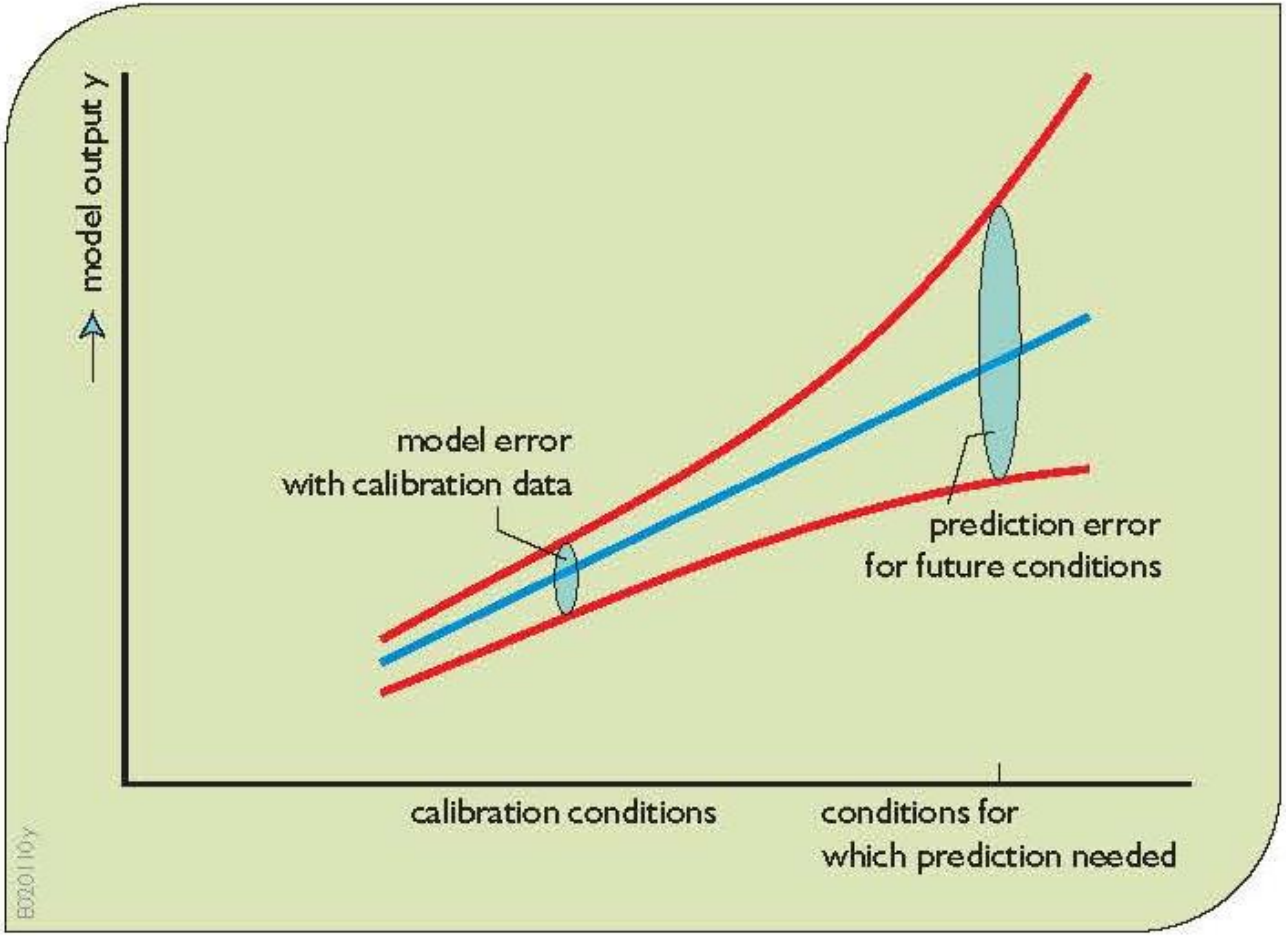
# Sensitivity - Uncertainty




Schematic diagram showing relationship among
model input parameter uncertainty and sensitivity to
model output variable uncertainty (Lal, 1995).

Loucks & van Beek, 2017

# Sensitivity - Uncertainty




The precision of model predictions is affected by the difference between the conditions or scenarios of interest and the conditions or scenarios for which the model was calibrated.

Loucks & van Beek, 2017

# Sensitivity - Uncertainty

Rather than contrasting ‘knowledge’ uncertainty versus natural variability versus decision uncertainty, one can classify uncertainty in another way based on specific sources of uncertainty, such as those listed below, and address ways of identifying and dealing with each source of uncertainty.

1. **Informational uncertainties**
   - imprecision in specifying the boundary and initial conditions that impact the output variable values
   - imprecision in measuring observed output variable values.

Loucks & van Beek, 2017

# Sensitivity - Uncertainty

2. **Model uncertainties**
   - uncertain model structure and parameter values
   - variability of observed input and output values over a region smaller than the spatial scale of the model
   - variability of observed model input and output values within a time smaller than the temporal scale of the model. (e.g., rainfall and depths and flows within a day)
   - errors in linking models of different spatial and temporal scales.
3. **Numerical errors**
   - errors in the model solution algorithm.

Loucks & van Beek, 2017

# Sensitivity - Uncertainty

## Monte Carlo

- A random variable is a variable that can have a set of different values generated by some probabilistic mechanism.
- Due to the complexity of physical systems and mathematical functions encountered in real-life hydrosystems design and management problems, derivation of the exact solution for the probabilistic characteristics of the system response is difficult, if not impossible.
- In such cases, Monte Carlo simulation (MCS) is a viable tool to provide numerical estimations of the stochastic features of the system response. MCS is a numerical procedure to reproduce random variables that preserves the specified distributional properties. In MCS, the system response of interest is repeatedly measured under various system parameter input sets generated from the known or assumed probabilistic laws. MCS offers a practical approach to the reliability analysis because the random behavior of the system response can be probabilistically duplicated.

Vijay et al., 2017

# Sensitivity - Uncertainty

## Monte Carlo

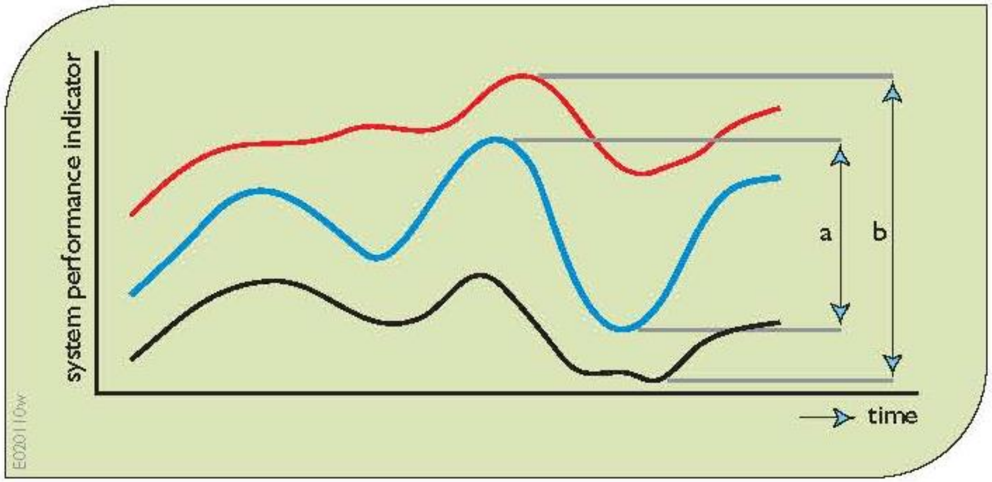
Two major concerns in the practical applications of MCS in uncertainty and reliability analyses are:

- (1) the requirement of a large amount of computations for generating random variates, and
- (2) the presence of correlation among stochastic basic parameters.

However, **as computing power increases**, the **concern with the computational cost diminishes**, and MCS is becoming more practical and viable for uncertainty and unreliability analyses. As noted previously, the accuracy of the model output statistics and probability distribution (e.g., probability that a specified safety level will be exceeded) obtained from MCS is a function of the number of simulations performed. For models or problems with a large number of stochastic basic variables and for which low probabilities (< 0.1) are of interest, tens of thousands of simulations may be required. Rules for determining the number of simulations required for convergence are not available, and, thus, replication of the MCS runs for a given number of simulations is the only way to check convergence (Melching, 1995).

Vijay et al., 2017

# Sensitivity - Uncertainty




Time series of model output or system performance showing variability over time. Range ‘a’ results from the natural variability of input data over time. The extended range ‘b’ results from the variability of natural input data as well as from imprecision in input data measurement, parameter value estimation, model structure and errors in model solution algorithms. The extent of this range will depend on the confidence level associated with that range.

Loucks & van Beek, 2017

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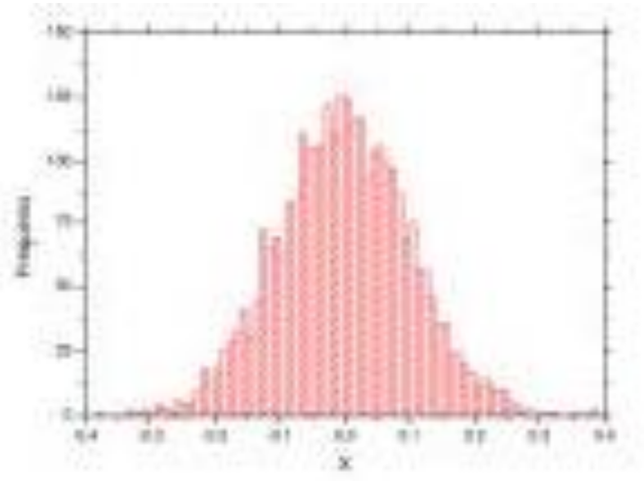
# Sensitivity - Uncertainty

## Simple Monte Carlo Sampling

The use of Monte Carlo simulation in solving general problems involving random variables (and/or stochastic processes) requires the generation of samples from random variable vector **X**. The most straightforward way of generating samples of a vector of random variables is by an inversion of their cumulative distribution function *F* (x). Generate a random vector of components uniformly distributed between 0 and 1;



dos Santos & Beck, 2014

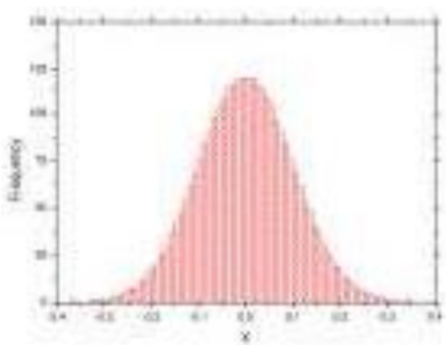
# Sensitivity - Uncertainty

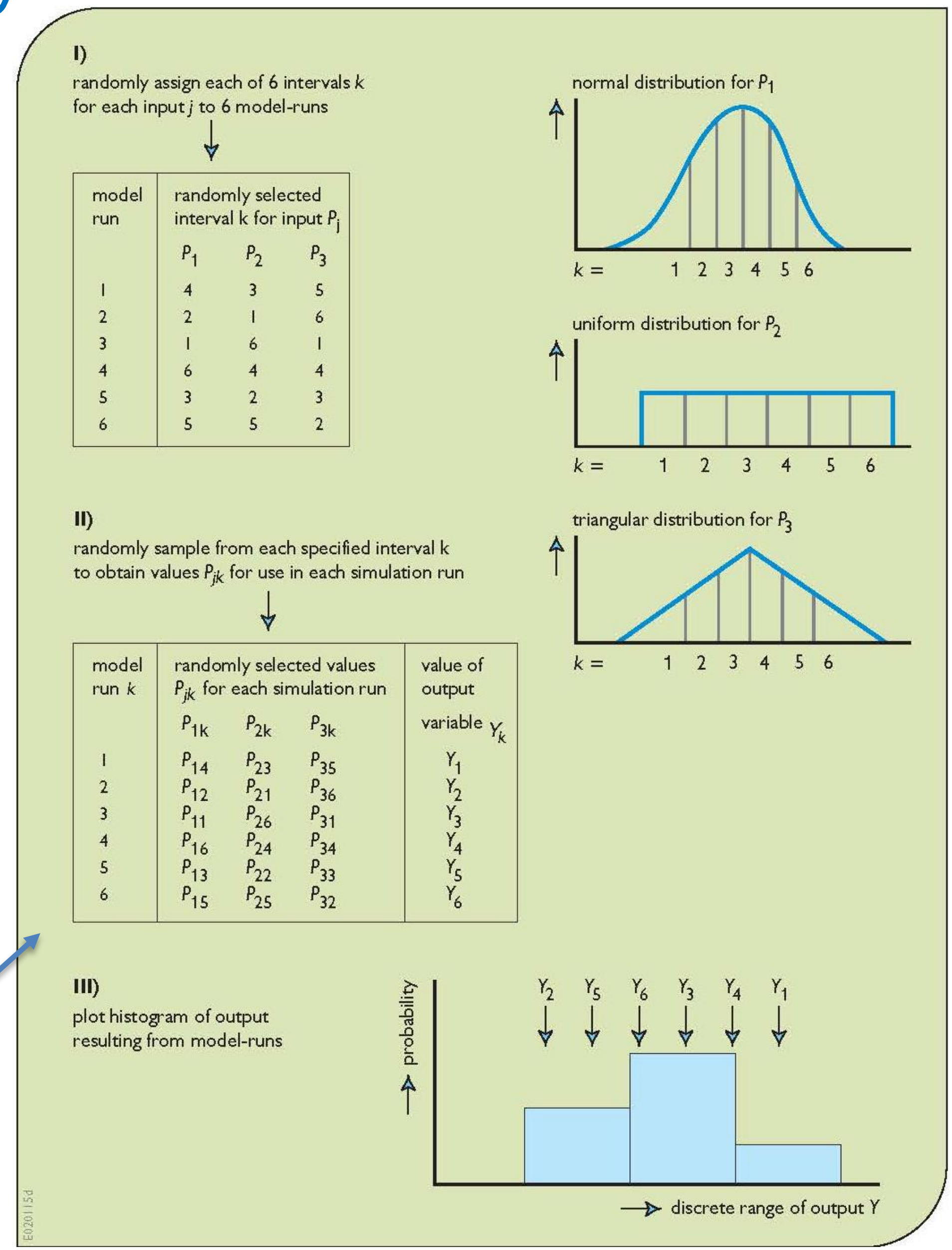
Loucks & van Beek, 2017

## Latin Hypercube Sampling

The Latin Hypercube Sampling (LHS) was introduced by McKay et al. (1979). The idea of Latin Hypercube Sampling is to divide the random variable domain in stripes, where each stripe is sampled only once. This procedure guarantees a sparse but homogeneous cover of the sampling space.

dos Santos & Beck, 2014



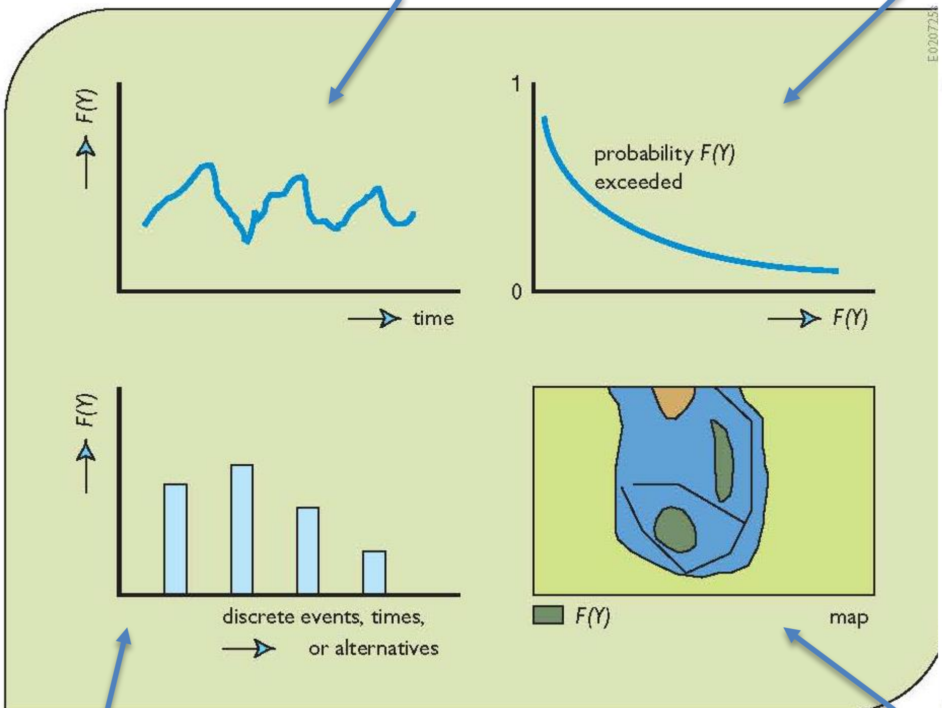


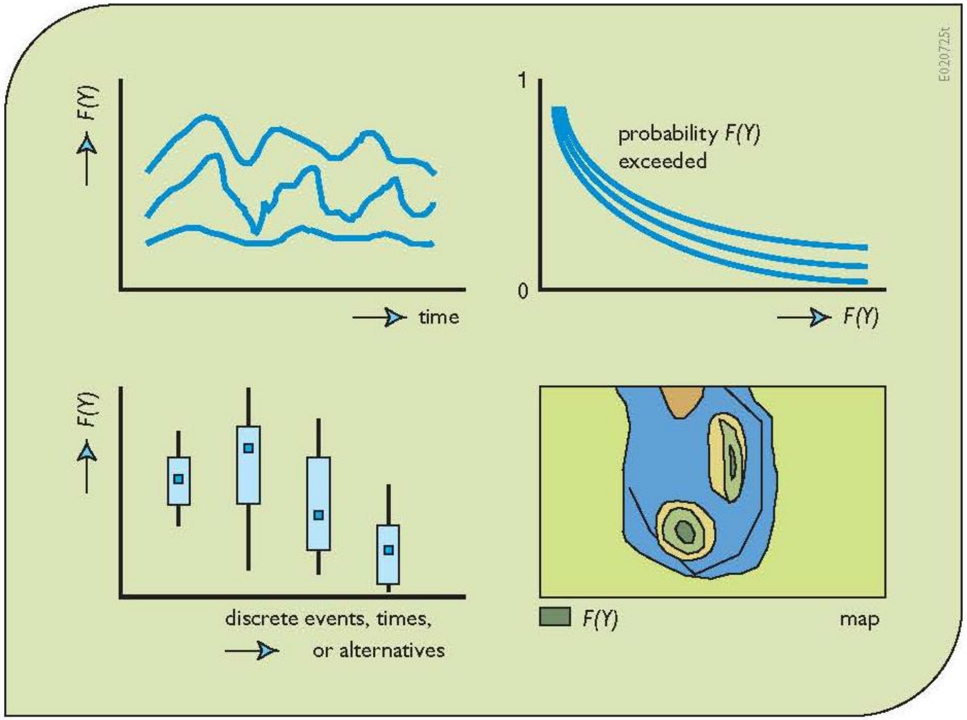

**Schematic representation of a Latin hypercube sampling procedure for six simulation runs.**

# Sensitivity - Uncertainty

time-series plots for continuous time-dependent indicators

probability exceedance distributions for continuous indicators




histograms for discrete event indicators

overlays on maps for space-dependent discrete events

Different types of displays used to show model output Y or system performance indicator values F (Y ).

Plots of ranges of possible model output Y or system indicator values F (Y ) for different types of displays.

Loucks & van Beek, 2017

- Sensitivity - Uncertainty
- **Sensitivity analysis application**
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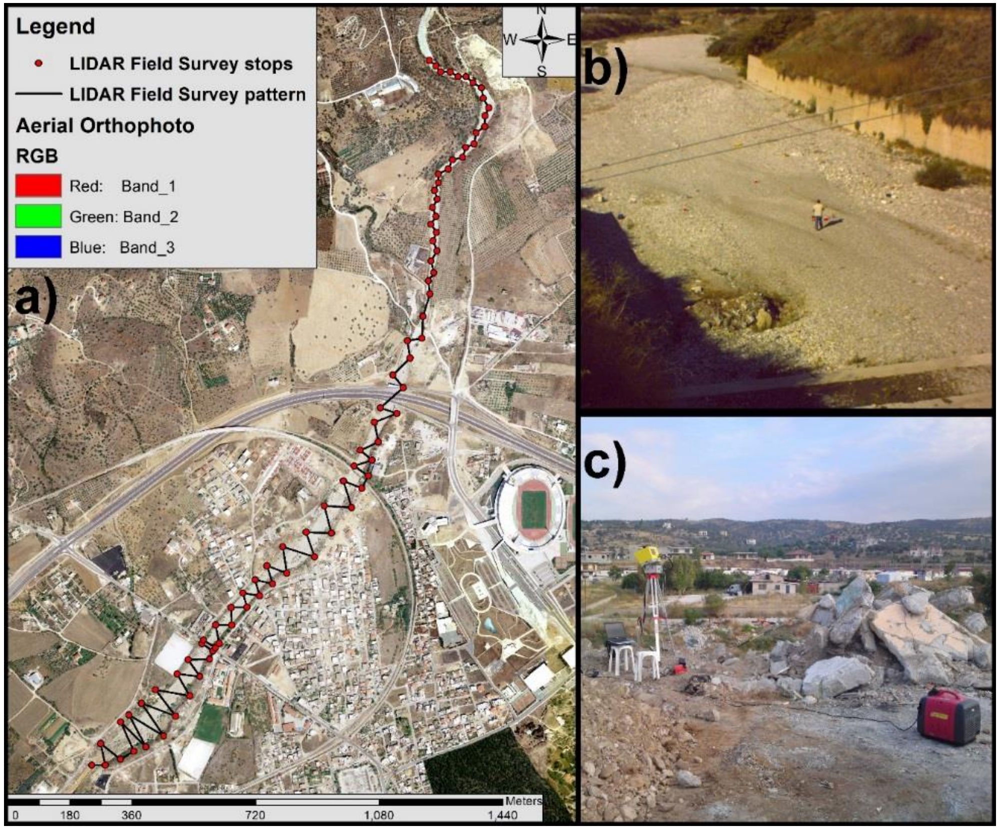
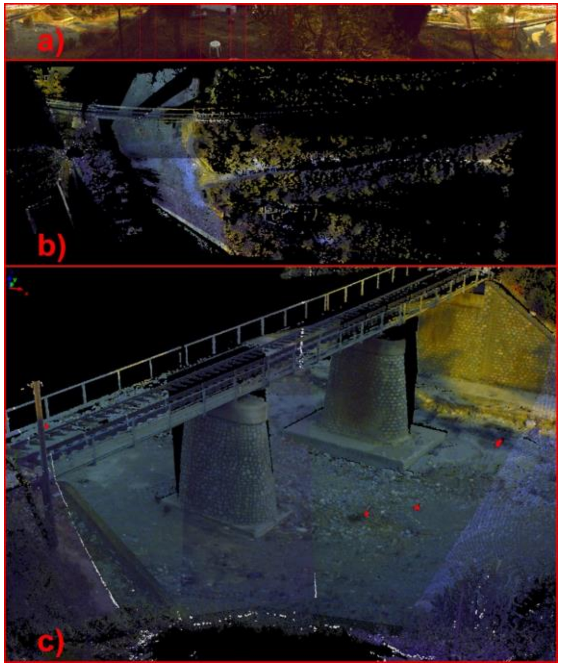
# LIDAR field survey

## LIDAR data collection

1)




2)




3)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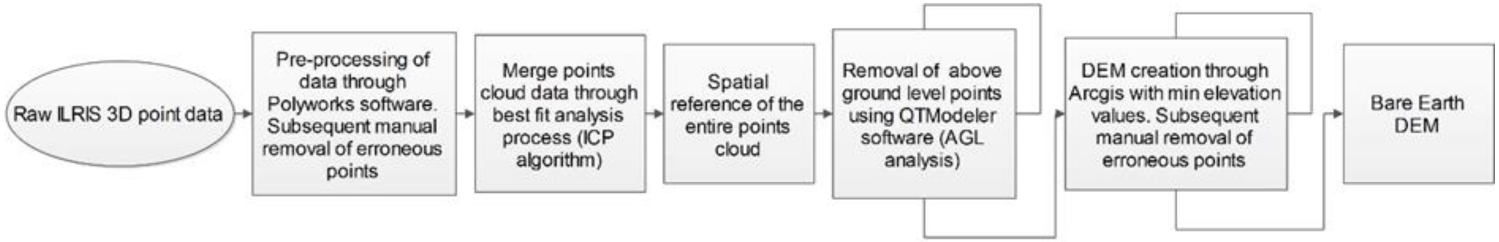
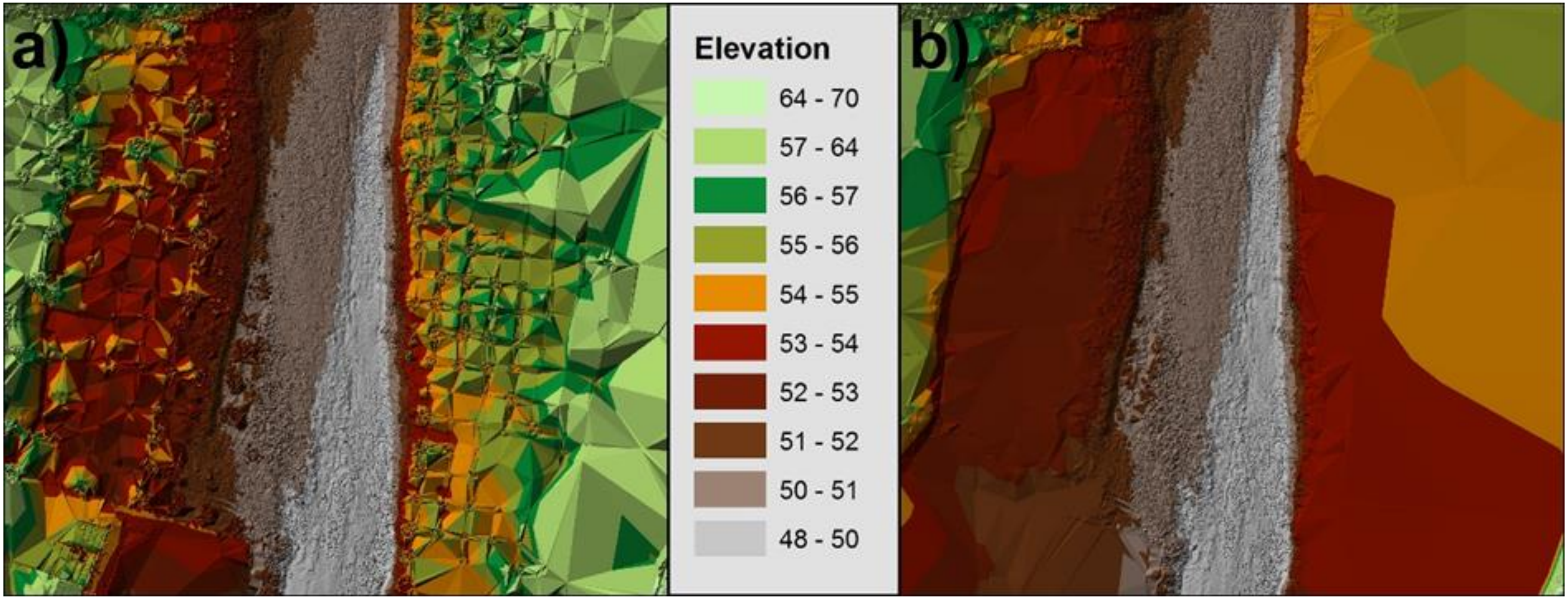
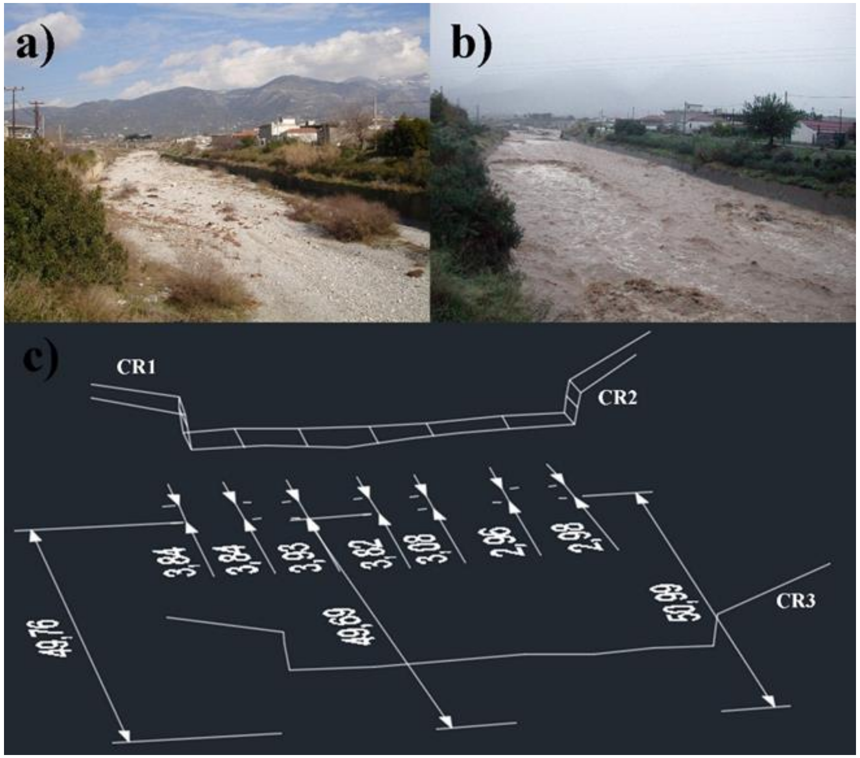
# LIDAR point cloud processing and Processed LIDAR DEM generation



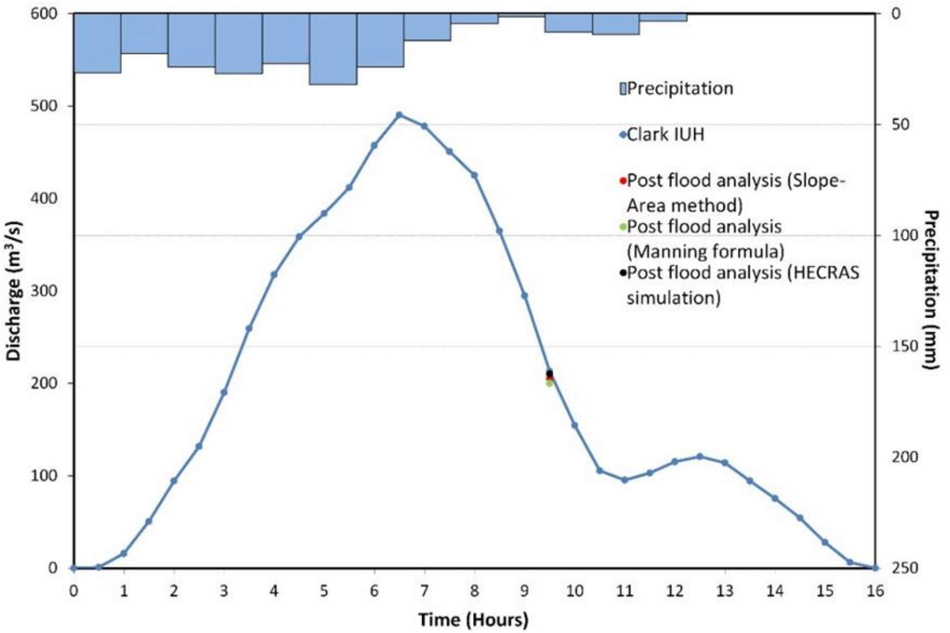

Papaioannou et al., 2013

# Post Flood Analysis




Roughness coefficient and flood hydrograph validation

- Slope Area method
- Manning Formula
- HEC-RAS hydraulic hydrodynamic modelling




Papaioannou et al., 2016

# Sensitivity analysis application

## Objectives

- to address the sensitivity of different modelling approaches in combination with several types of river and riverine spatial resolution on floodplain mapping and flood inundation modelling at ungauged streams.
  - using different DEM created by Terrestrial Laser Scanning (TLS) point cloud data, classic land surveying and digitization of elevation contours from 1:5000 scale topographic maps
  - using various hydraulic models of different complexity
- to demonstrate the methodology for Xerias watershed, Thessaly, Greece

Papaioannou et al., 2016

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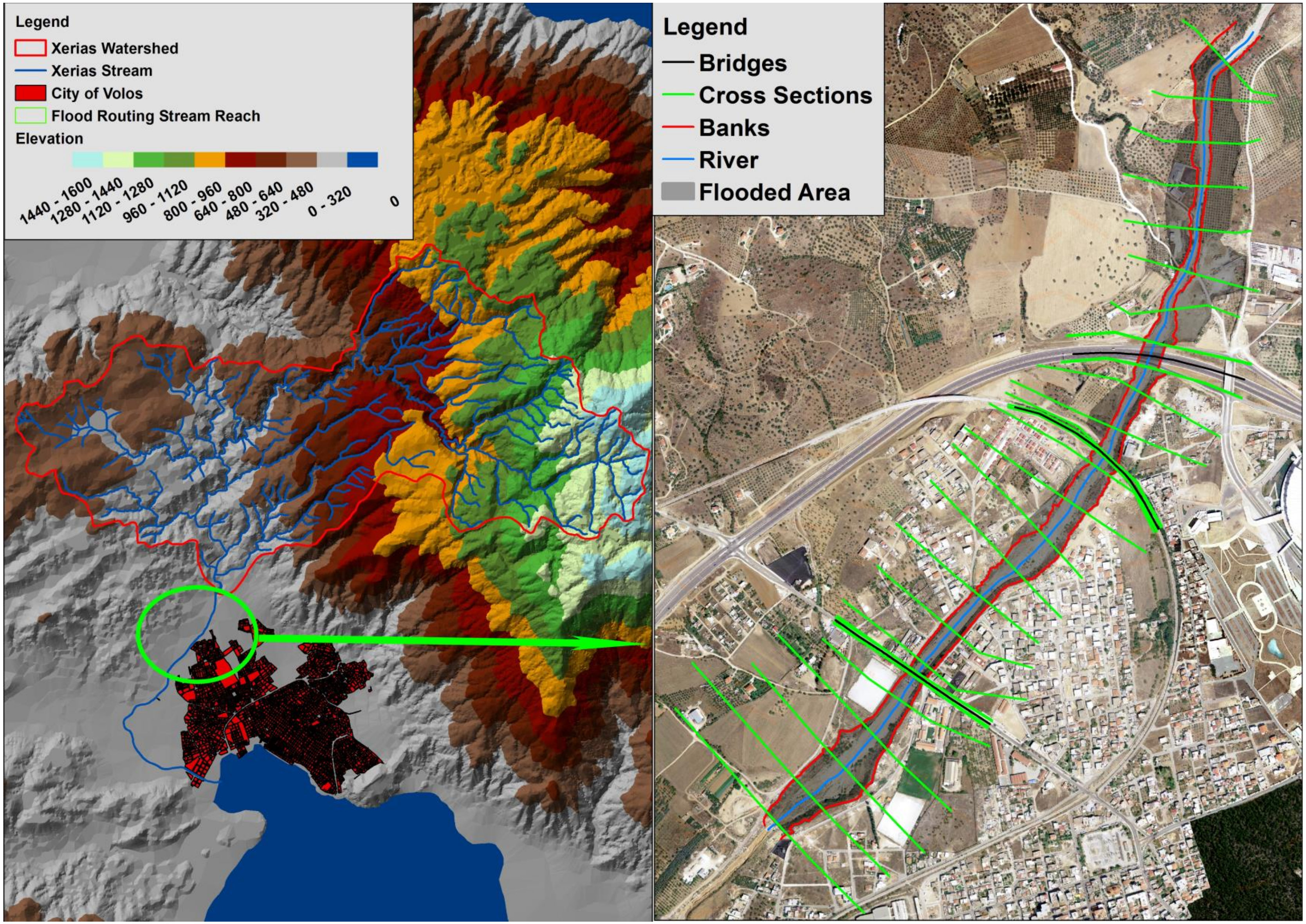
# Study Watershed and Flood Routing Stream Reach




Papaioannou et al., 2016

# Configuration processes

## Modelling approach

- 1D (16 configurations)
- 2D (26 configurations)
- Coupled (1D/2D) (23 configurations)

## Dem accuracy

- Processed LIDAR DEM
- Raw LIDAR DEM
- Topographical surveying DEM
- Digitized 1:5000 map DEM

## Validation process

| Event simulated | Event Observed | | |
|---|---|---|---|
| | Yes | No | Total |
| Yes | $A_c$ (Hit) | $B_c$ (False alarm) | $A_c + B_c$ |
| No | $C_c$ (Miss) | $D_c$ (Correct rejections) | $C_c + D_c$ |
| Total | $A_c + C_c$ | $B_c + D_c$ | $A_c+B_c+C_c+D_c$ |

$$CSI = \frac{A_c}{(A_c + B_c + C_c)}$$

$A_c$ = Hit - event simulated to occur, and did occur;

$B_c$ = False alarm - event simulated to occur, but did not occur and;

$C_c$ = Miss - event simulated not to occur, but did occur

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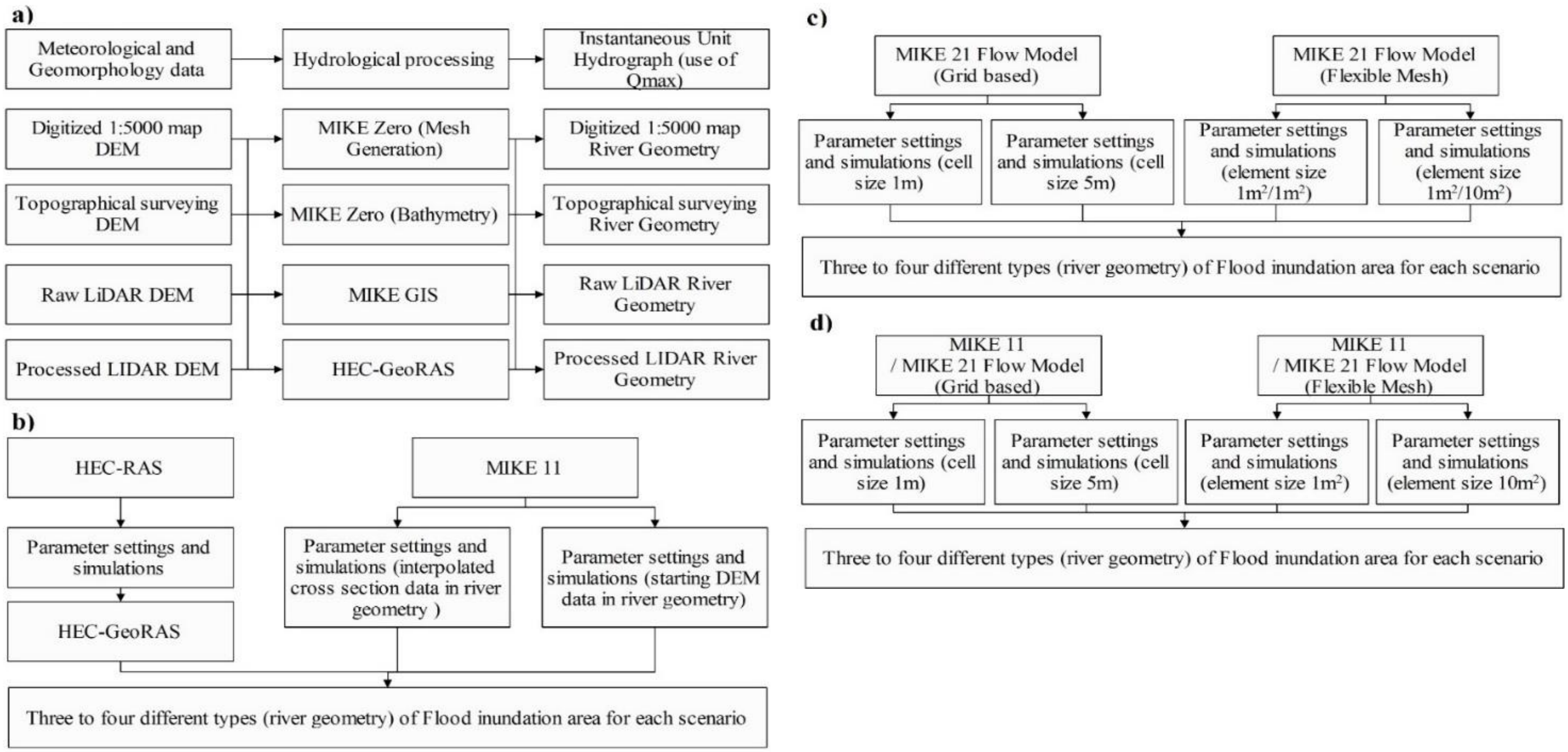
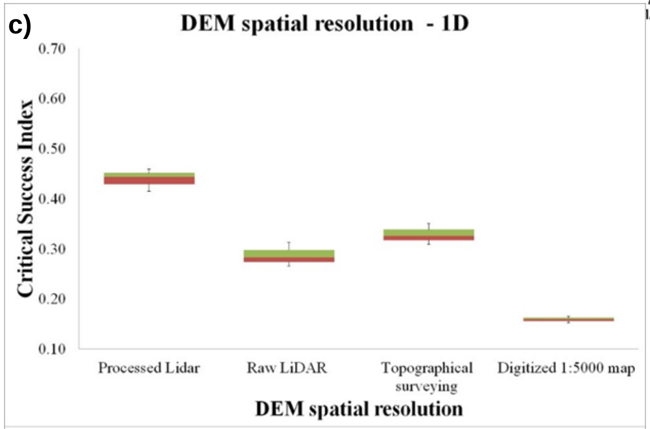
# First level of sensitivity analysis (Dem accuracy – Modelling approach)

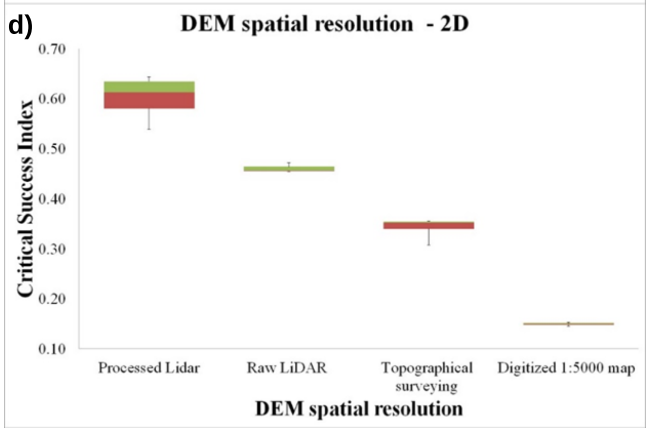


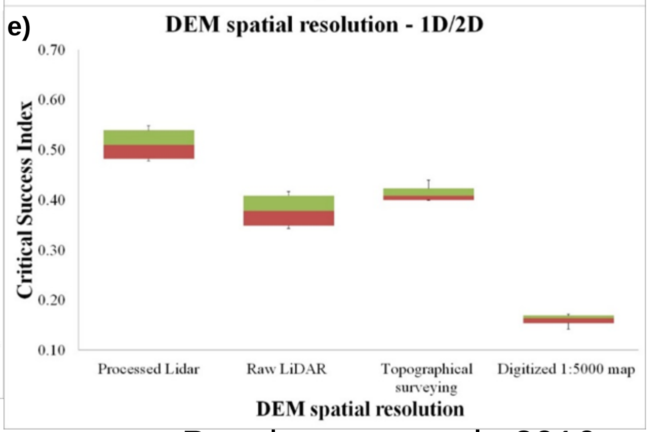

Papaioannou et al., 2016

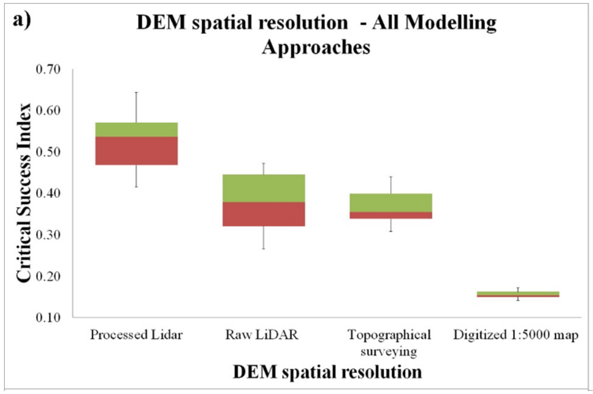
# Results- First level of sensitivity

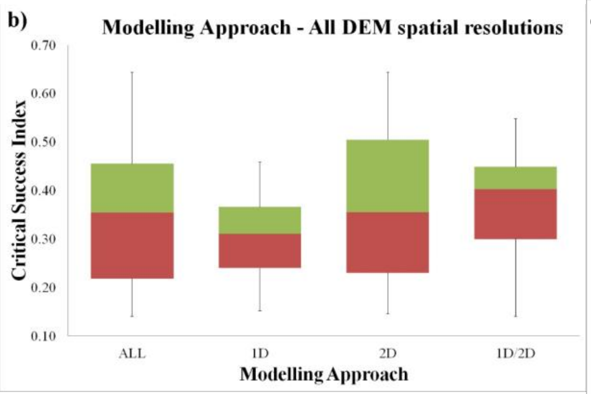
| | 1D | | | |
|---|---|---|---|---|
| | HEC-RAS | MIKE11 Interpolated cross section | MIKE 11 DEM | |
| Processed Lidar | **0.46** | 0.41 | 0.44 | |
| Raw LiDAR | **0.31** | 0.27 | 0.28 | |
| Topographical surveying | 0.33 | 0.31 | **0.35** | |
| Digitized 1:5000 map | **0.17** | 0.16 | 0.15 | |
| | **2D** | | | |
| | MIKE 21 Flow Model 1m cell size | MIKE 21 Flow Model 5m cell size | MIKE 21 Flow Model Flexible mesh $1m^2/1m^2$ | MIKE 21 Flow Model Flexible mesh $1m^2/10m^2$ |
| Processed Lidar | **0.64** | 0.63 | 0.59 | 0.54 |
| Raw LiDAR | - | 0.45 | 0.46 | **0.47** |
| Topographical surveying | 0.35 | **0.36** | 0.31 | 0.35 |
| Digitized 1:5000 map | 0.15 | 0.15 | 0.15 | 0.15 |
| | **1D/2D** | | | |
| | MIKE11 / MIKE 21 Flow Model 1m cell size | MIKE11 / MIKE 21 Flow Model 5m cell size | MIKE11 / MIKE 21 Flow Model Flexible mesh $1m^2/1m^2$ | MIKE11 / MIKE 21 Flow Model Flexible mesh $1m^2/10m^2$ |
| Processed Lidar | 0.54 | **0.55** | 0.48 | 0.48 |
| Raw LiDAR | 0.41 | **0.42** | 0.34 | 0.35 |
| Topographical surveying | **0.44** | 0.42 | 0.40 | 0.40 |
| Digitized 1:5000 map | 0.16 | 0.14 | **0.17** | **0.17** |

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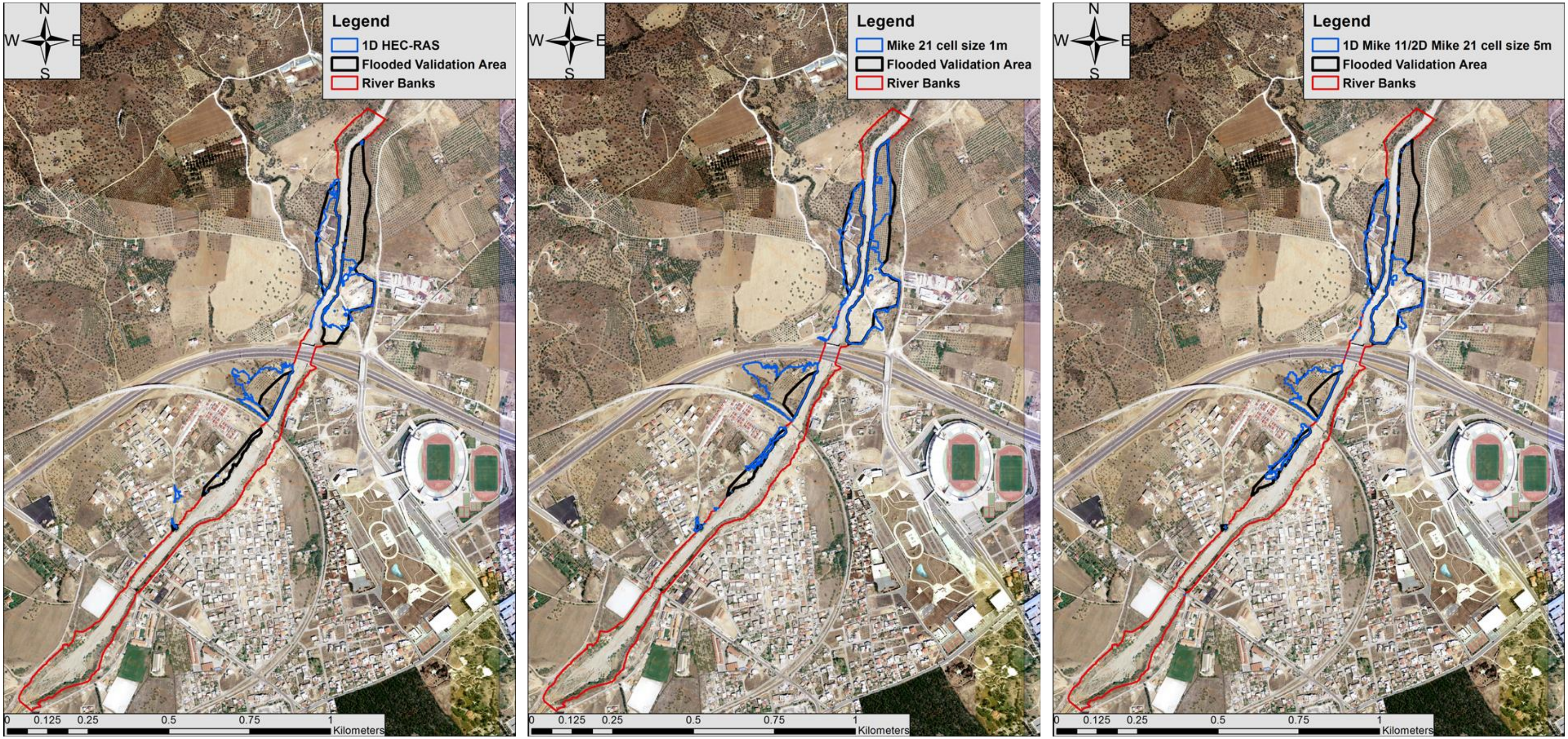
# Results- First level of sensitivity

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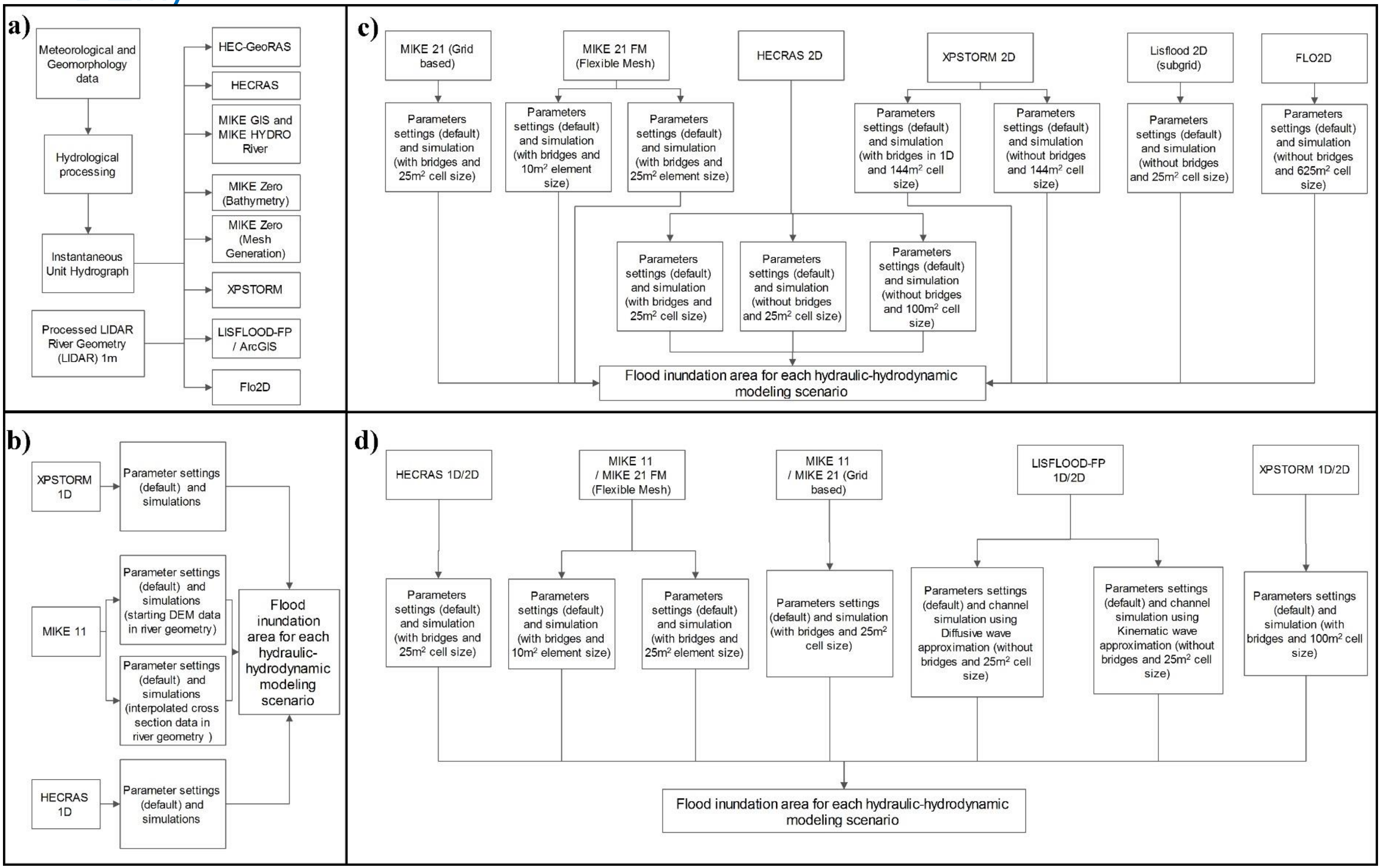
# Second level of sensitivity analysis (Modelling approach-LIDAR DEM)

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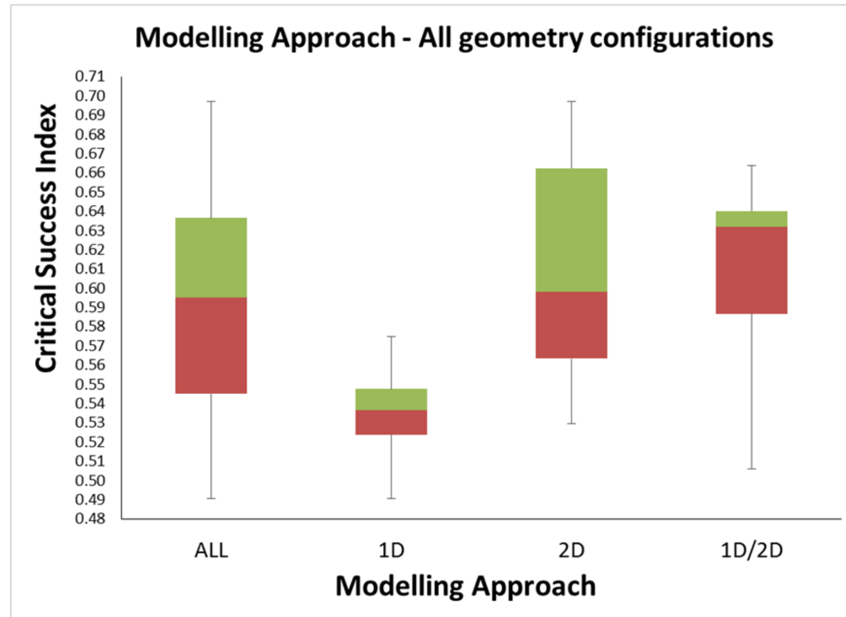
# Results- Second level of sensitivity

| | | | | | |
|---|---|---|---|---|---|
| | | **1D** | | | |
| Hydraulic model | XPSTORM 1D | MIKE11 (Interpolated DEM) | MIKE11 (DEM) | HEC-RAS 1D | |
| CSI | 0.49 | 0.54 | **0.57** | 0.53 | |
| | | **2D** | | | |
| Hydraulic model | XPSTORM 2D (144m² - bridges) | XPSTORM 2D (144m² - without bridges) | MIKE21 HD (25m² - bridges) | MIKE 21 HD FM (25m² - bridges) | MIKE 21 HD FM (10m² - bridges) |
| CSI | 0.58 | 0.53 | 0.60 | 0.60 | 0.56 |
| Hydraulic model | LISFLOOD-FP 2D subgrid (25m² - without bridges) Quasi-2D | HEC-RAS 2D (100m² - without bridges) | HEC-RAS 2D (25m² - without bridges) | HEC-RAS 2D (25m² - bridges) | FLO2D (625m² - without bridges) |
| CSI | **0.70** | **0.70** | 0.68 | 0.60 | 0.56 |
| | | **1D/2D** | | | |
| Hydraulic model | XPSTORM 1D/2D (100m²) | MIKE11/MIKE21 HD (25m²) | MIKE11/MIKE21 HD FM (25m²) | MIKE11/MIKE21 HD FM (10m²) | HEC-RAS 1D/2D (25m²) |
| CSI | 0.51 | 0.64 | **0.66** | 0.63 | 0.64 |
| Hydraulic model | LISFLOOD-FP (Diffusive wave-channel/ without bridges/ 25m² in floodplain) | LISFLOOD-FP (Kinematic wave-channel / without bridges/ 25m² in floodplain) | | | |
| CSI | 0.63 | 0.54 | | | |

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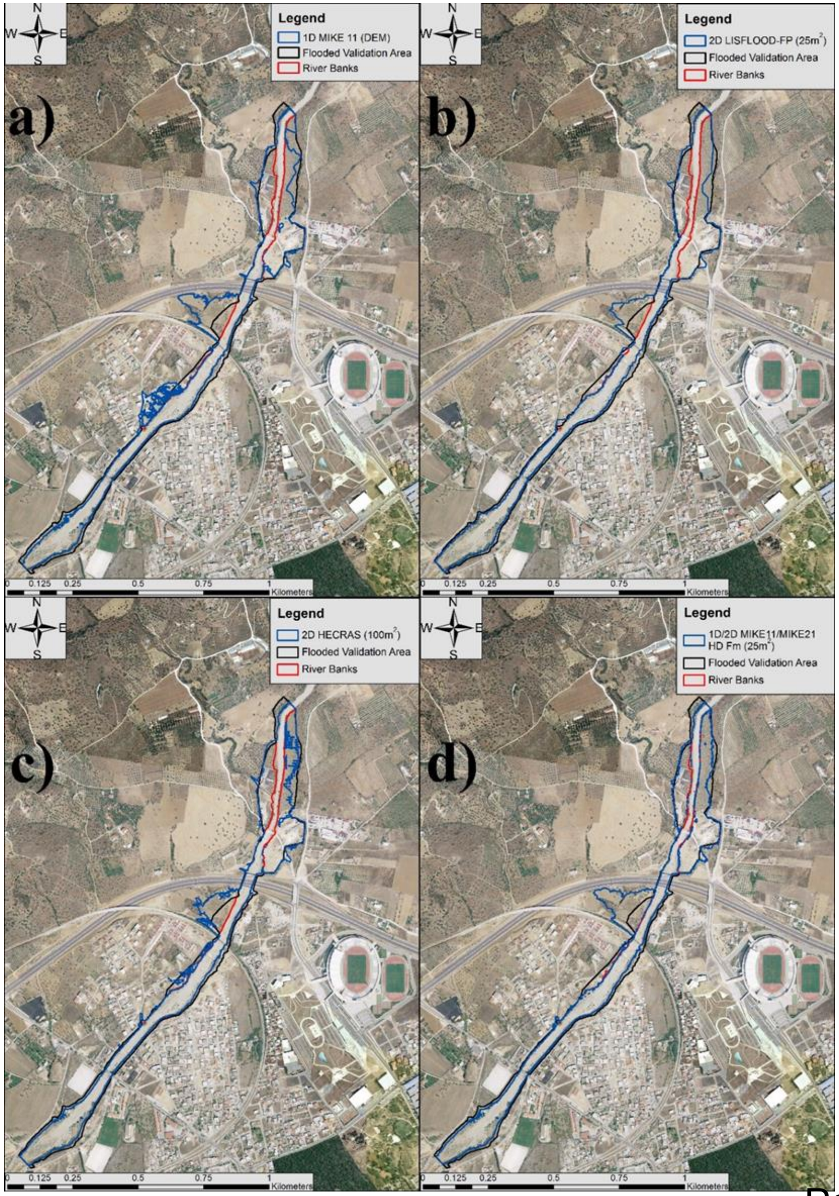
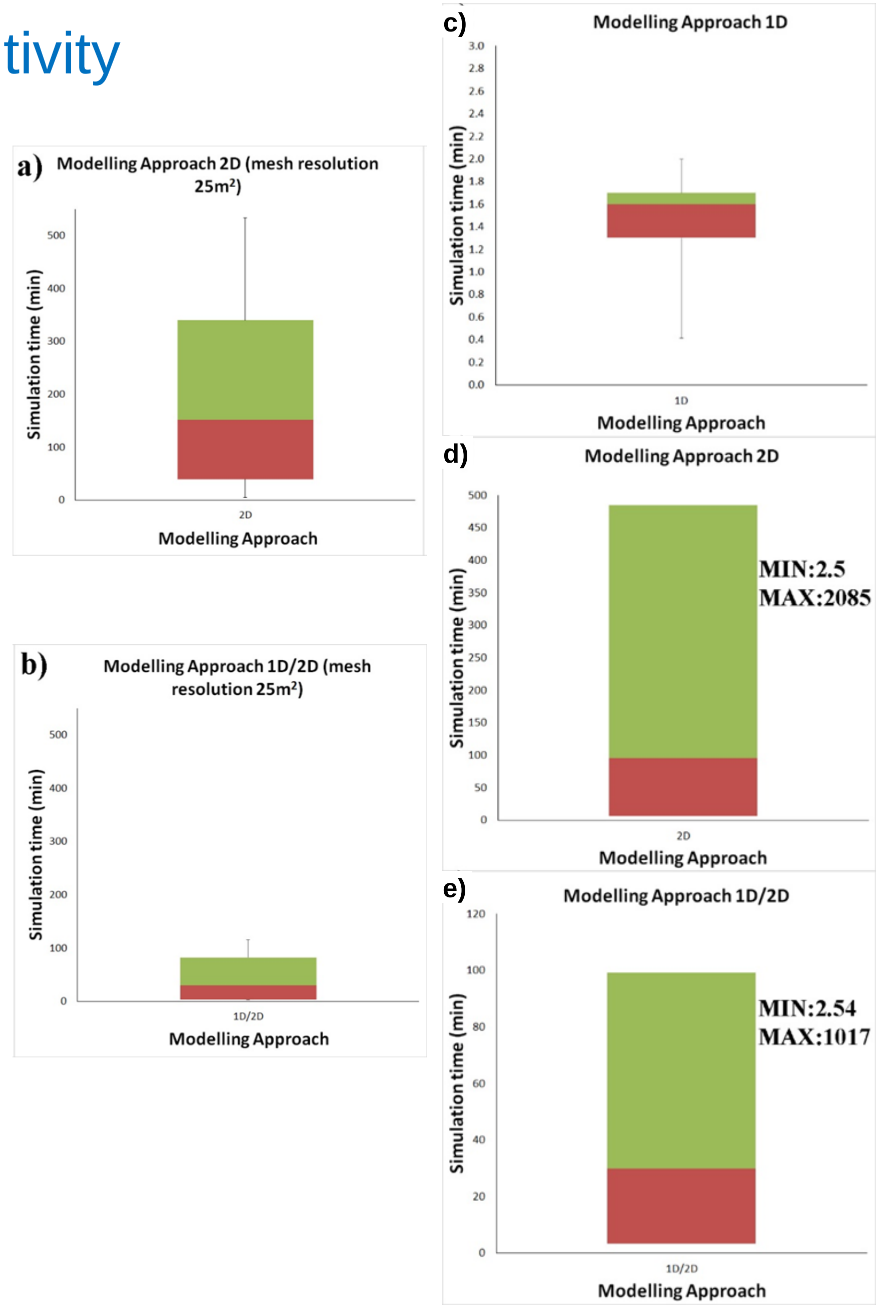
# Results- Second level of sensitivity




Papaioannou, 2017a

# Results- Second level of sensitivity

| | | | | | |
|---|---|---|---|---|---|
| | | **1D** | | | |
| Hydraulic model | XPSTORM 1D | MIKE11 (Interpolated DEM) | MIKE11 (DEM) | HEC-RAS 1D | |
| sim time (min) | **0.42** | 1.60 | 1.60 | 2.00 | |
| | | | **2D** | | |
| Hydraulic model | XPSTORM 2D (144m² - bridges) | XPSTORM 2D (144m² - without bridges) | MIKE21 HD (25m² - bridges) | MIKE 21 HD FM (25m² - bridges) | MIKE 21 HD FM (10m² - bridges) |
| sim time (min) | **2.50** | 2.52 | 340.00 | 533.00 | 1380.00 |
| Hydraulic model | LISFLOOD-FP 2D subgrid (25m² - without bridges) Quasi-2D | HEC-RAS 2D (100m² - without bridges) | HEC-RAS 2D (25m² - without bridges) | HEC-RAS 2D (25m² - bridges) | FLO2D (625m² - without bridges) |
| sim time (min) | **5.18** | 10.40 | 39.37 | 152.00 | 2085.00 |
| | | | **1D/2D** | | |
| Hydraulic model | XPSTORM 1D/2D (100m²) | MIKE11/MIKE21 HD (25m²) | MIKE11/MIKE21HD FM (25m²) | MIKE11/ MIKE 21 HD FM (10m²) | HEC-RAS 1D/2D (25m²) |
| sim time (min) | **2.54** | 30.00 | 116.00 | 1017.00 | 82.47 |
| Hydraulic model | LISFLOOD-FP (Diffusive wave-channel/ without bridges/ 25m² in floodplain) | LISFLOOD-FP (Kinematic wave-channel / without bridges/ 25m² in floodplain) | | | |
| sim time (min) | 3.90 | **2.90** | | | |

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# Concluding Remarks

- HEC-RAS 1D is proposed for calibration and uncertainty analysis investigation.
  - inline structures
  - simulation time
  - accuracy of the results
  - data pre and post processing
  - availability of the model (free, commercial use)
  - encoding of the model (open source, closed code)

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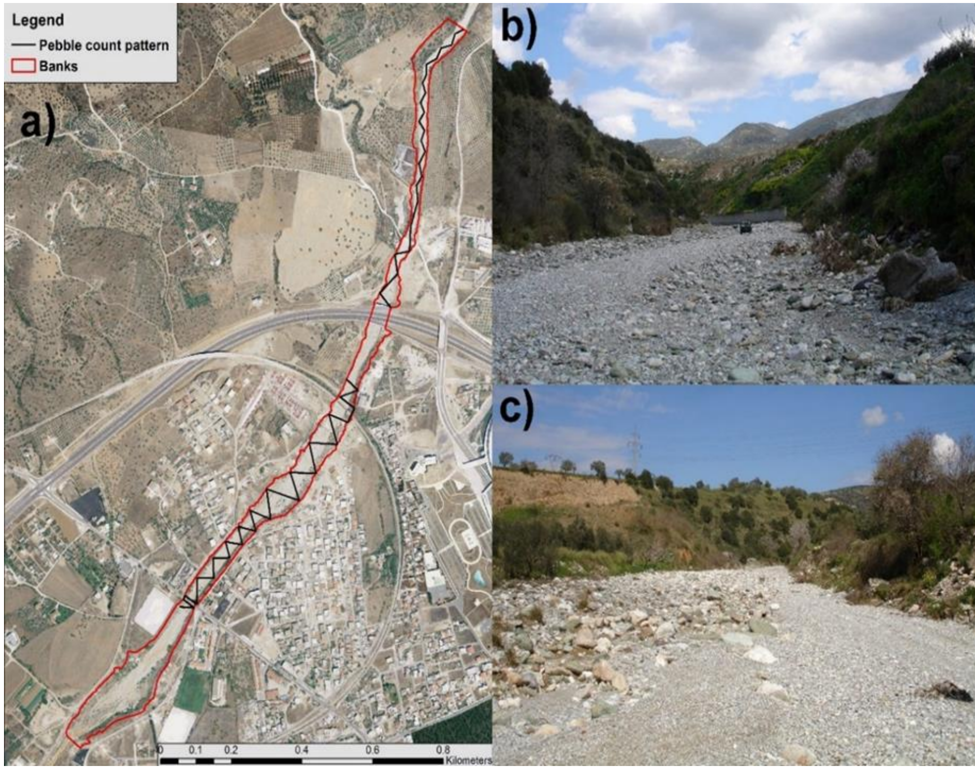
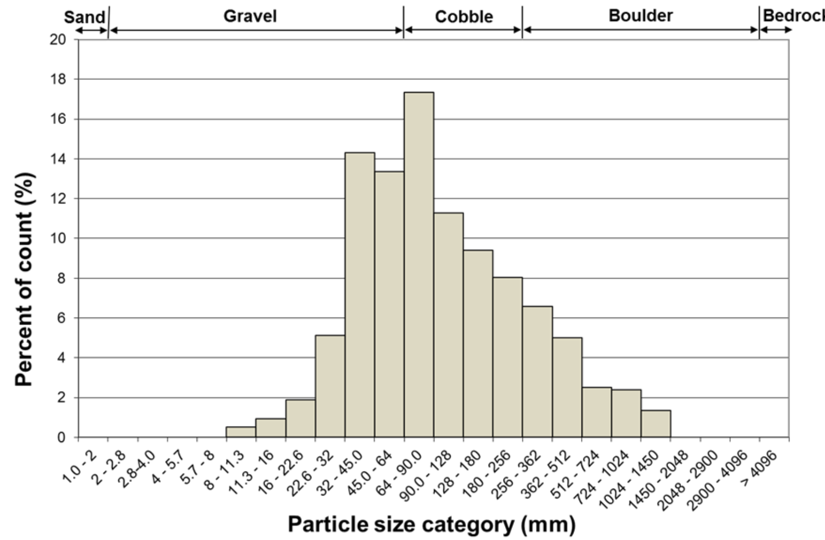
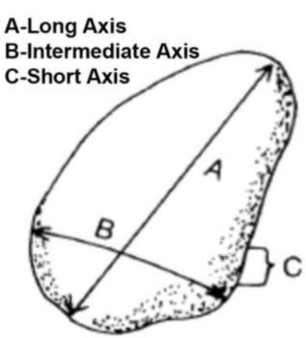
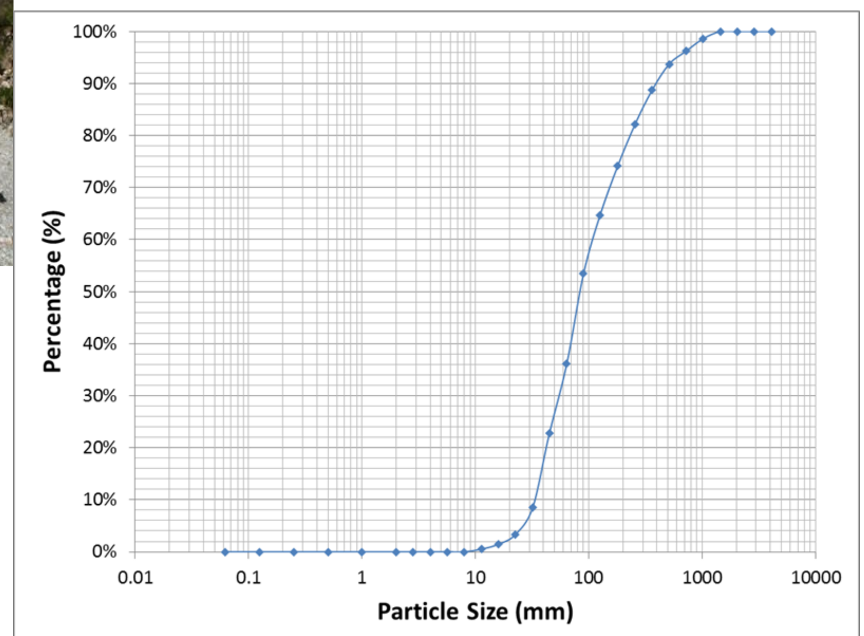
- Sensitivity - Uncertainty
- Sensitivity analysis application
- **Uncertainty analysis application using monte carlo**

# Wolman Pebble Count




Papaioannou et al., 2017b

# Wolman Pebble Count

| A/A | Equation | Roughness (*n*) Coefficient Value | Source |
|---|---|---|---|
| 1 | $n = \frac{1}{(2.1 + 2.3x + 6\ln(10.8vR))}$ | 0.035 | Gwinn and Re 1980 |
| 2 | $n = \frac{0.1129R^{1/6}}{1.16 + 2\log\left({R}/{D_{84}}\right)}$ | 0.043 | Marcus et al. 1992 |
| 3 | $n = 0.0326 + 1.3041S_W$ | 0.052 | Loukas and Qu 1996 |
| 4 | $n = 0.322S_{fr}^{0.38}R^{-0.16}$ | 0.074 | Romero et al 2010 |
| 5 | $n = \left[0.183 + \ln\left(\frac{1.762S_{fr}^{0.1581}}{Fr^{0.2631}}\right)\right]\left(\frac{D_{84}^{0.167}}{\sqrt{g}}\right)$ | 0.074 | Romero et al 2010 |
| 6 | $n = (n_0 + n_1 + n_2 + n_3 + n_4)m$ | 0.103 | Jarret, 1985 |
| 7 | $n = (n_0 + n_1 + n_2 + n_3 + n_4)m$ | 0.074 | Jarret, 1985 |
| 8 | $n = 0.121(S_W)^{0.38}(R)^{0.08}$ | 0.061 | Chang, 2012 |
| 9 | Base scenario estimated using guidelines of Chow (1959)<br>Extreme case scenario using guidelines of Chow (1959) | 0.106<br>0.12 | Chow, 1959 |
| 10 | $n = 0.104(S_W)^{0.177}$ | 0.049 | Chang, 2012 |
| 11 | $n = \frac{D_{90}^{1/6}}{15.29}$ | 0.056 | Ho and Huan 1992 |
| 12 | $n = \frac{D_{90}^{1/6}}{16}$ | 0.054 | Ho and Huan 1992 |
| 13 | $n = 0.0593D_{50}^{0.179}$ | 0.038 | Javan et al., 19 |
| 14 | $n = 0.0561D_{65}^{0.179}$ | 0.039 | Javan et al., 19 |
| 15 | $n = 0.0495D_{90}^{0.16}$ | 0.043 | Javan et al., 19 |
| 16 | $n = 0.0431D_{90}^{1/6}$ | 0.037 | McKay and Fischenich, 20 |
| 17 | $n = 0.0439D_{90}^{1/6}$ | 0.038 | McKay and Fischenich, 20 |
| 18 | $n = \left[0.183 + \ln\left(\frac{1.7462S_{fr}^{0.1581}}{Fr^{0.2631}}\right)\right]\frac{(D_{84})^{1/6}}{\sqrt{g}}$ | 0.072 | Ugarte and Madrid-Aris, 1 |
| 19 | $n = \left[0.183 + \ln\left(\frac{1.3014S_{fr}^{0.0785}\left(\frac{R}{D_{84}}\right)^{0.0211}}{Fr^{0.1705}}\right)\right]\frac{(D_{84})^{1/6}}{\sqrt{g}}$ | 0.076 | Ugarte and Madrid-Aris, 1 |
| 20 | $n = \left[0.219 + \ln\left(\frac{1.3259S_{fr}^{0.0932}\left(\frac{R}{D_{50}}\right)^{0.026}}{Fr^{0.2054}}\right)\right]\frac{(D_{50})^{1/6}}{\sqrt{g}}$ | 0.075 | Ugarte and Madrid-Aris, 1 |
| 21 | Optimum value according to calibration process | 0.09 | |

n = Manning's n roughness coefficient ($m^3$/s), x = retardance class, v= velocity (m/s), R = hydraulic radius (m), $D_i$ = characteristic size of bed material which is larger than i% of particles (m), Sw = water surface slope (m/m), $S_{fr}$ = energy sl (m/m), Fr = Froude number, g = acceleration due to gravity (m/$s^2$).

| Predefined diameters | $d_s$, (mm) |
|---|---|
| $d_{16}$ | 38.86 |
| $d_{35}$ | 62.41 |
| $d_{50}$ | 84.83 |
| $d_{75}$ | 188.39 |
| $d_{84}$ | 285.81 |
| $d_{90}$ | 400.13 |
| $d_{95}$ | 618.88 |

## Assumptions

- Energy gradient = River bed gradient
- Optimum roughness value
- Median of the total estimated hydraulic parameters

Papaioannou et al., 2017b

# Uncertainty analysis application using monte carlo

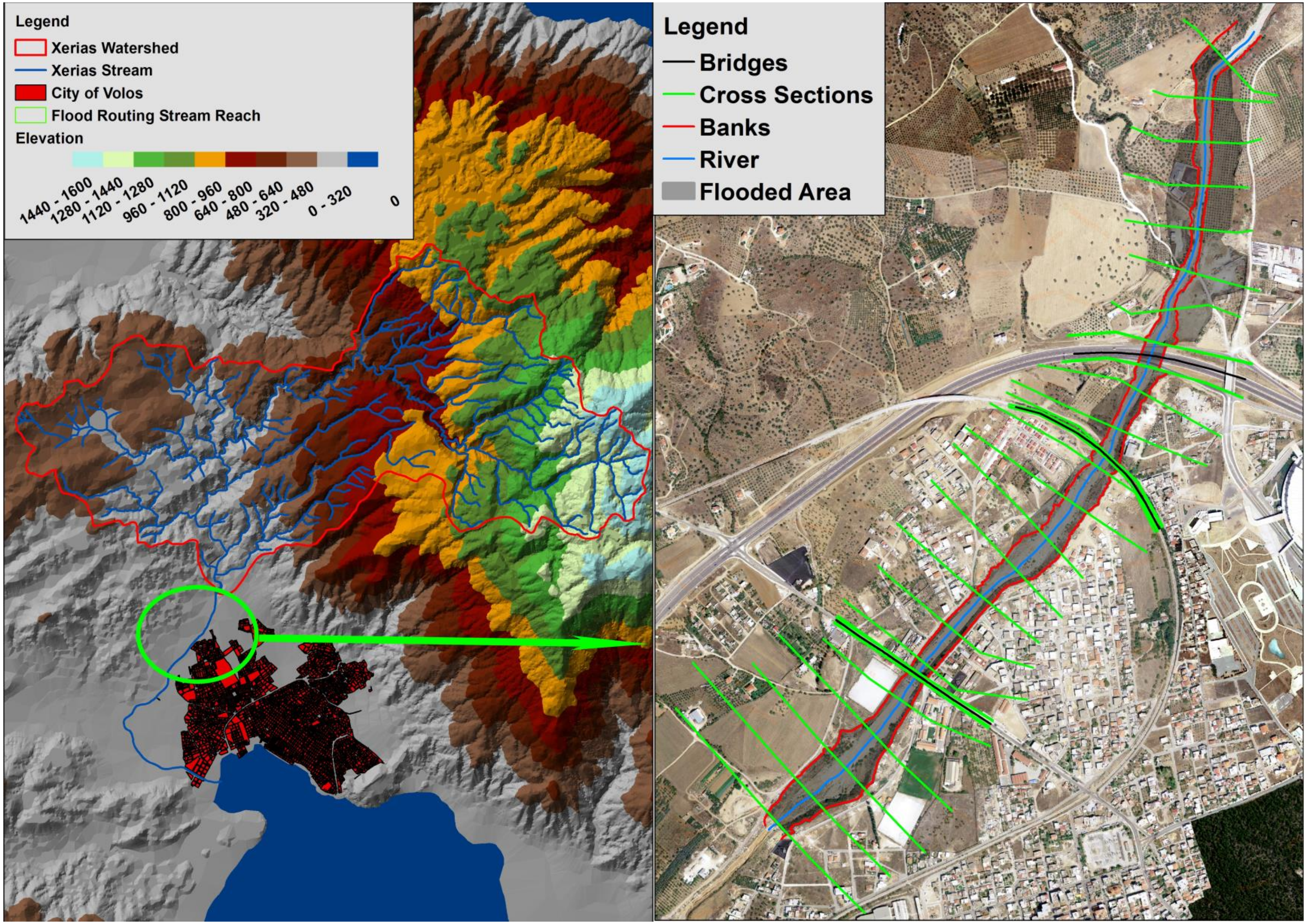
## Objectives

- to develop a Monte Carlo framework (for ungauged streams) for uncertainty analysis of floodplain mapping due to roughness coefficient.

- Steps
  - to evaluate the ability of using a one dimensional hydraulic-hydrodynamic model and GIS to produce probability maps of flood plain areas for ungauged catchments and flash flood events
  - to use typical processes to determine the size distribution of river bed material, empirical formulas, several probability distributions and the Latin Hypercube Sampling algorithm to generate different sets of Manning roughness coefficients.
  - to demonstrate the methodology for the ungauged Xerias River, Volos, Greece.

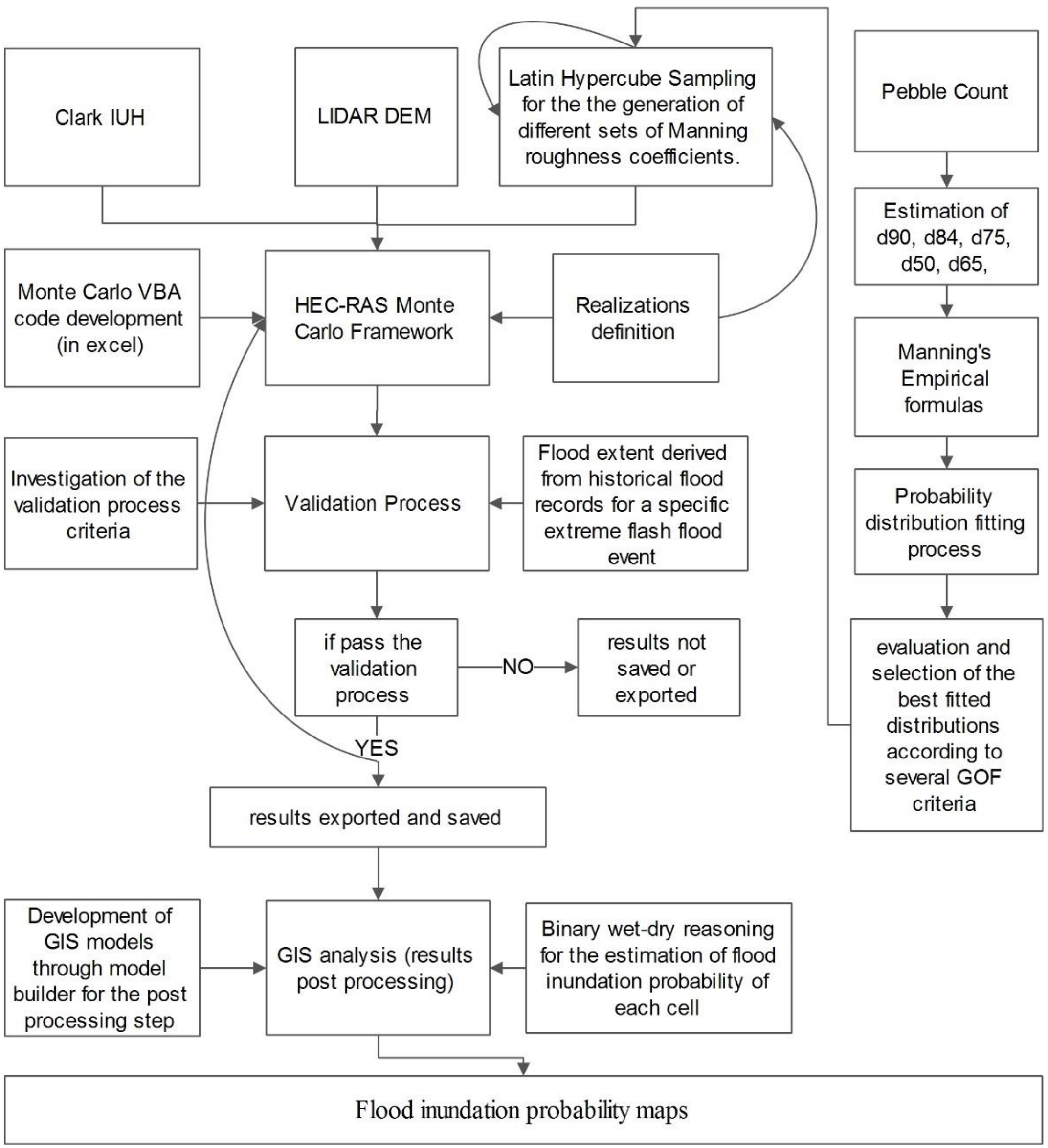
Papaioannou, 2017a / Papaioannou et al.,2017b, 2017c

# Study Watershed and Flood Routing Stream Reach




Papaioannou et al.,2017b

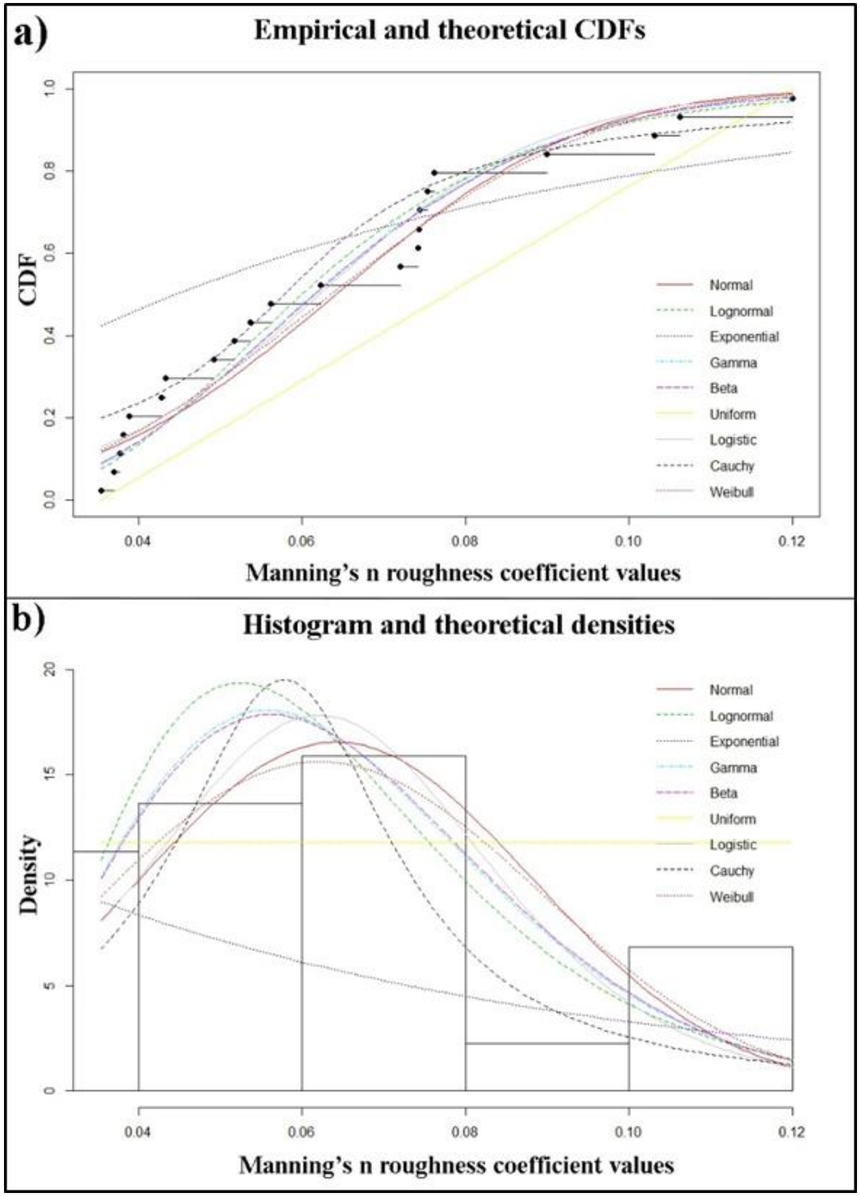
# Methodology




Papaioannou et al.,2017b

# Distribution fitting

| Distributions | Goodness of fit statistics | | | Goodness of fit criteria | |
|---|---|---|---|---|---|
| | Kolmogorov-Smirnov | Cramer-von Mises | Anderson - Darling | AIC | BIC |
| Normal | 0.1307 | 0.1008 | 0.6818 | 97.5191 | -95.337 |
| **Lognormal** | 0.1458 | 0.0793 | 0.5153 | **101.437** | **-99.2552** |
| Exponential | 0.4239 | 0.8333 | 4.1749 | 74.8262 | -73.7352 |
| **Gamma** | 0.131 | 0.08 | 0.5303 | **100.762** | **-98.5796** |
| Beta | 0.1304 | 0.0801 | 0.5327 | 100.673 | -98.4905 |
| **Uniform** | 0.3358 | 0.7077 | inf | NA | NA |
| Logistic | 0.1292 | 0.0867 | 0.625 | 96.6285 | -94.4465 |
| Cauchy | 0.2002 | 0.137 | 0.9604 | 87.7592 | -85.5771 |
| **Weibull** | 0.1296 | 0.0848 | 0.5794 | **98.6621** | **-96.48** |

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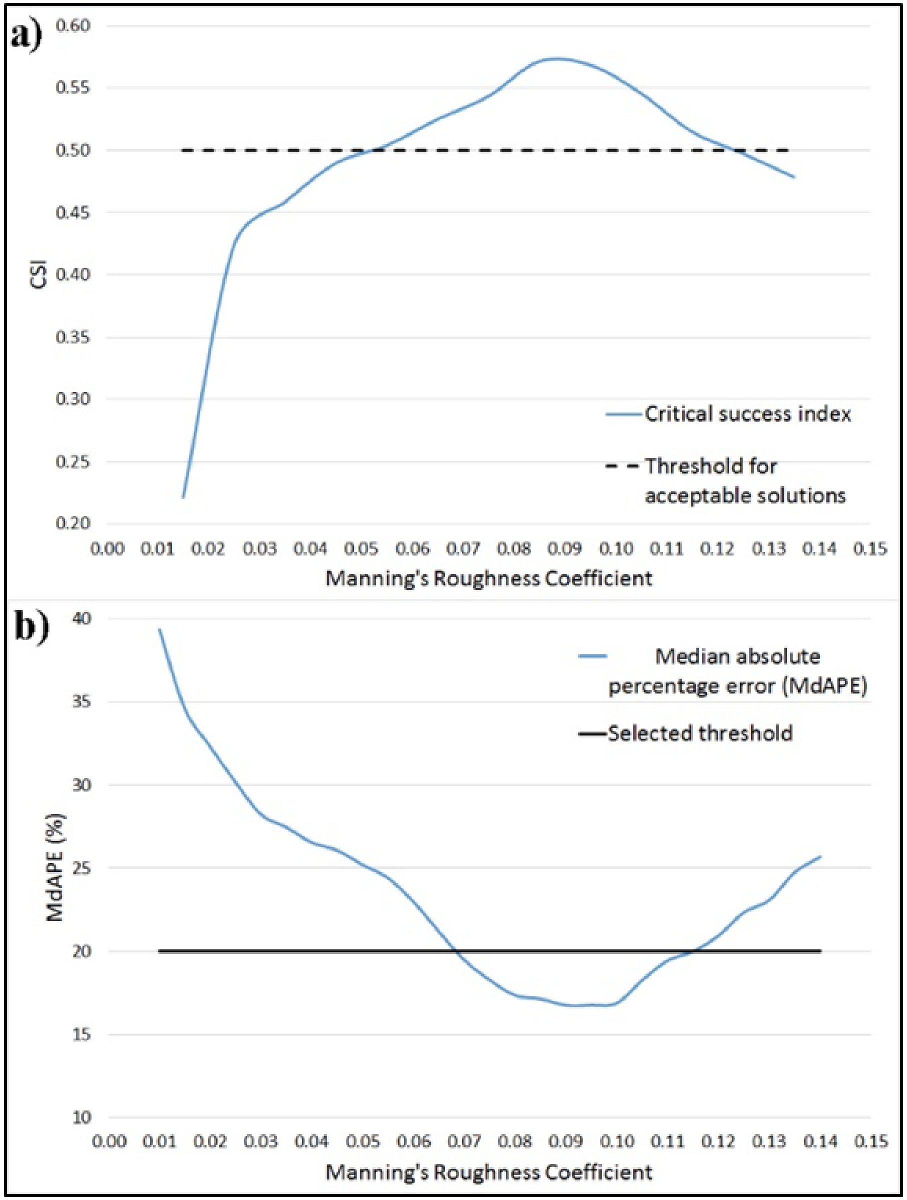
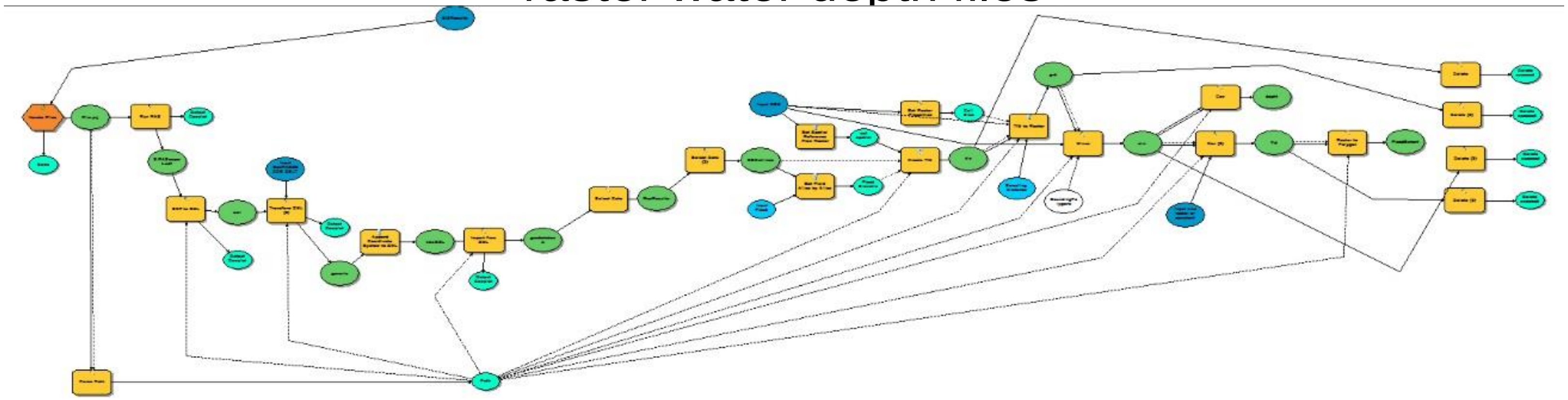
# Validation process



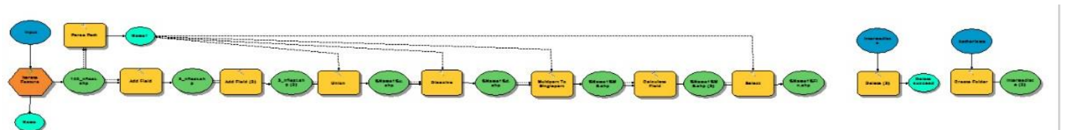

Papaioannou ,2017a

# GIS Analysis

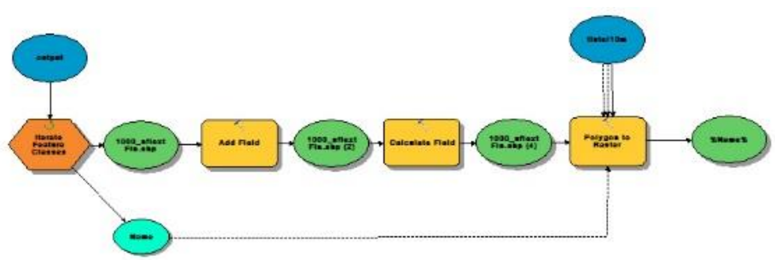
Model1 for HEC-RAS results transformation to flood extent polygons and raster water depth files



Model2 for the post processing of the flood extent polygons



Model3 for the creation of the raster probability maps



Papaioannou ,2017a

# Flood Inundation Probability Maps

- For the creation of the flood inundation probability maps a binary wet-dry reasoning selected in order to estimate the flood inundation probability of each cell.
- Moreover, all the probability maps that created by the selected realization set are summed to create the total one.
- The probability maps created by dividing the total with the number of ensemble members.
- Finally for computational purposes the probability maps were classified in 10 probability classes : 0-10%, 10-20%, 20-30%, 30-40%, 40-50%, 50-60%, 60-70%, 70-80%, 80-90%, 90-100%.

Papaioannou et al., 2017c

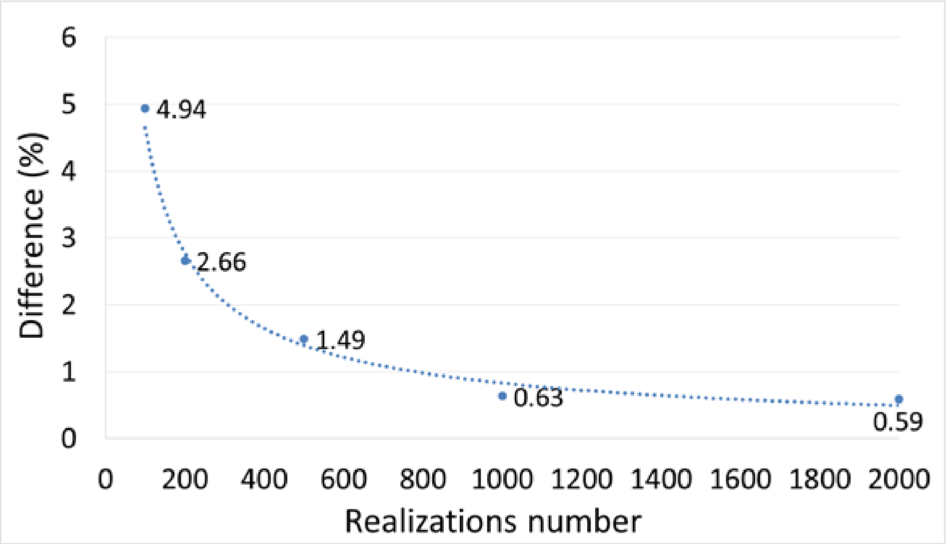
# Stability and Sensitivity of the Method

- Different realizations set applied : 100, 200, 500, 1000, 2000, 5000.
- Lognormal distribution was used for all the realizations numbers.
- Gamma, Weibull and Uniform distributions were also examined for 1000 realizations.
- Two different validation threshold setups were examined : 22%, 18%.
- Five supplementary river geometry conditions examined with distance between the cross sections of : 2 m, 4 m, 8 m, 16 m, 32 m.
- Stability of the component has been examined using the optimum configuration. Five different runs have been employed and the results are compared.

Papaioannou et al., 2017c

# Results

| Number of acceptable realizations | 100 | 200 | 500 | 1000 | 2000 | 5000 |
|---|---|---|---|---|---|---|
| 100 | 0 | | | | | |
| 200 | 5.31 | 0 | | | | |
| 500 | 5.15 | 1.88 | 0 | | | |
| 1000 | 4.71 | 3.14 | 1.84 | 0 | | |
| 2000 | 4.57 | 2.75 | 1.44 | 0.60 | 0 | |
| 5000 | **4.94** | **2.66** | **1.49** | **0.63** | **0.59** | **0** |

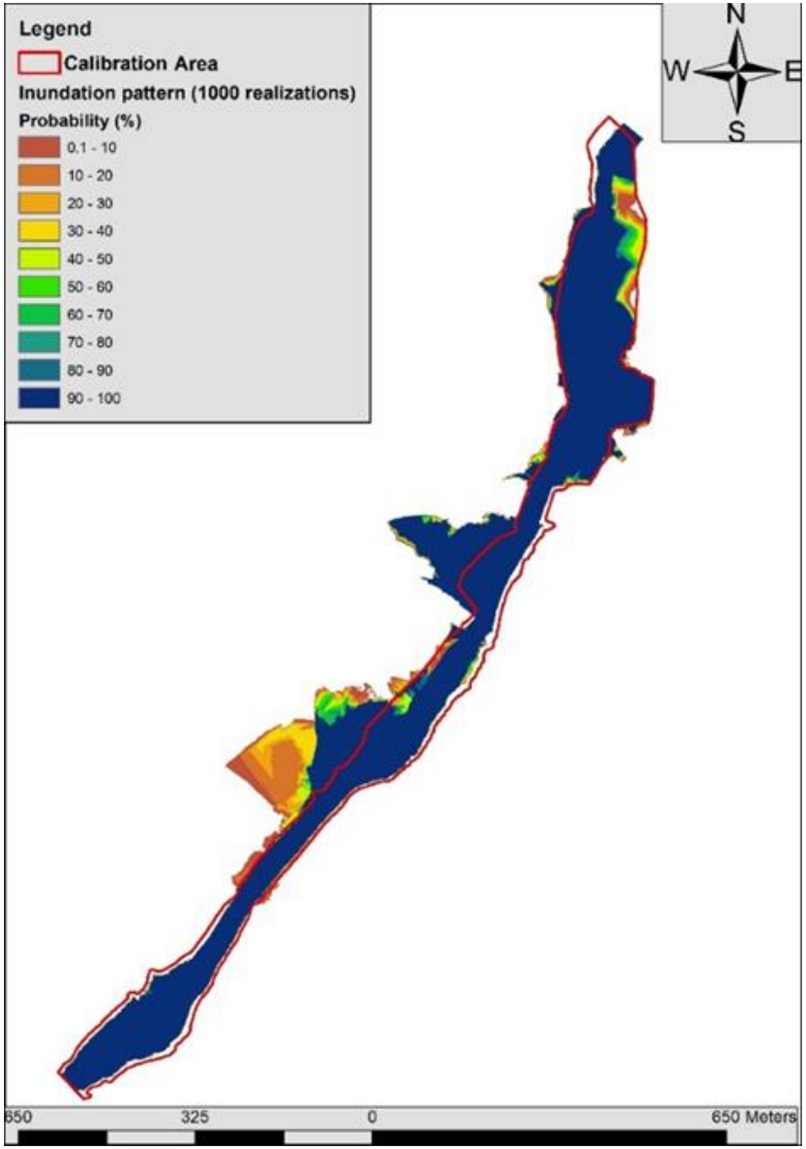


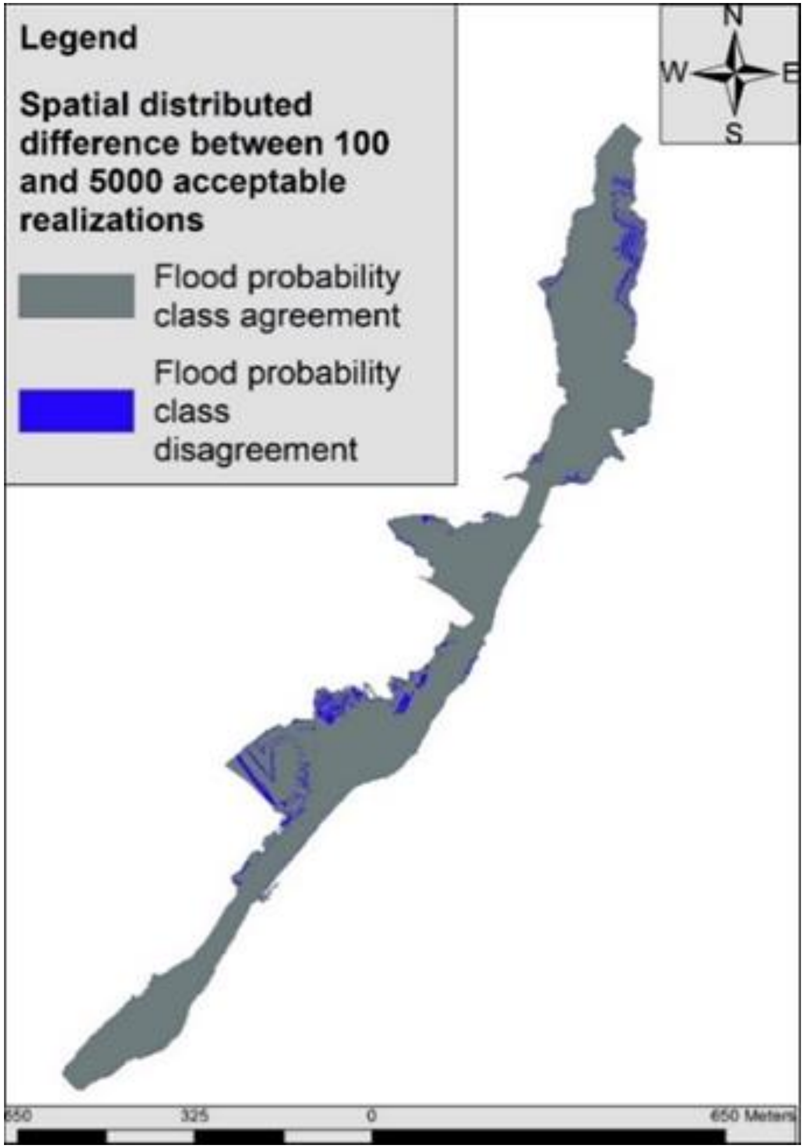

## Realizations inspection: flood inundation probabilities classes

| Flood inundation probabilities classes (%) \Number of acceptable Realizations | 100 | 200 | 500 | 1000 | 2000 | 5000 |
|---|---|---|---|---|---|---|
| 100-90 | 78.72 | 79.34 | 78.82 | 78.87 | 78.83 | 78.83 |
| 90-80 | 0.70 | 0.96 | 1.06 | 0.98 | 1.02 | 0.93 |
| 80-70 | 0.95 | 0.97 | 0.90 | 0.84 | 0.83 | 0.96 |
| 70-60 | 0.81 | 1.36 | 1.14 | 1.23 | 1.19 | 1.28 |
| 60-50 | 1.43 | 1.63 | 1.49 | 1.38 | 1.32 | 1.29 |
| 50-40 | 1.72 | 1.29 | 1.72 | 1.65 | 1.73 | 1.65 |
| 40-30 | 3.16 | 2.78 | 3.04 | 2.72 | 2.89 | 2.86 |
| 30-20 | 3.58 | 2.78 | 2.45 | 2.72 | 2.78 | 2.65 |
| 20-10 | 5.33 | 5.74 | 5.20 | 5.06 | 4.84 | 4.96 |
| 10-0 | 3.61 | 3.16 | 4.18 | 4.56 | 4.57 | 4.58 |

Papaioannou et al., 2017c

# Results




Papaioannou et al., 2017c

# Results

| Theoretical Probability Distributions differences (%) | Lnorm | Gamma | Weibull | Uniform |
|---|---|---|---|---|
| Lnorm | **0** | | | |
| Gamma | **1.53** | 0 | | |
| Weibull | **4.48** | 3.23 | 0 | |
| Uniform | **19.22** | 19.31 | 18.92 | 0 |

## Distributions inspection: flood inundation probabilities classes distribution in percent (%)

| Flood inundation probabilities classes (%) \ Theoretical Probability Distributions | Lognormal | Gamma | Weibull | Uniform |
|---|---|---|---|---|
| **100-90** | 78.87 | 78.85 | 79.16 | 79.61 |
| **90-80** | 0.98 | 0.94 | 1.08 | 1.85 |
| **80-70** | 0.84 | 1.01 | 1.09 | 2.14 |
| **70-60** | 1.23 | 1.27 | 1.46 | 2.28 |
| **60-50** | 1.38 | 1.30 | 1.41 | 2.84 |
| **50-40** | 1.65 | 1.73 | 1.66 | 2.19 |
| **40-30** | 2.72 | 3.18 | 2.72 | 3.78 |
| **30-20** | 2.72 | 2.42 | 2.45 | 2.29 |
| **20-10** | 5.06 | 4.69 | 4.96 | 1.35 |
| **10-0** | 4.56 | 4.61 | 4.01 | 1.68 |

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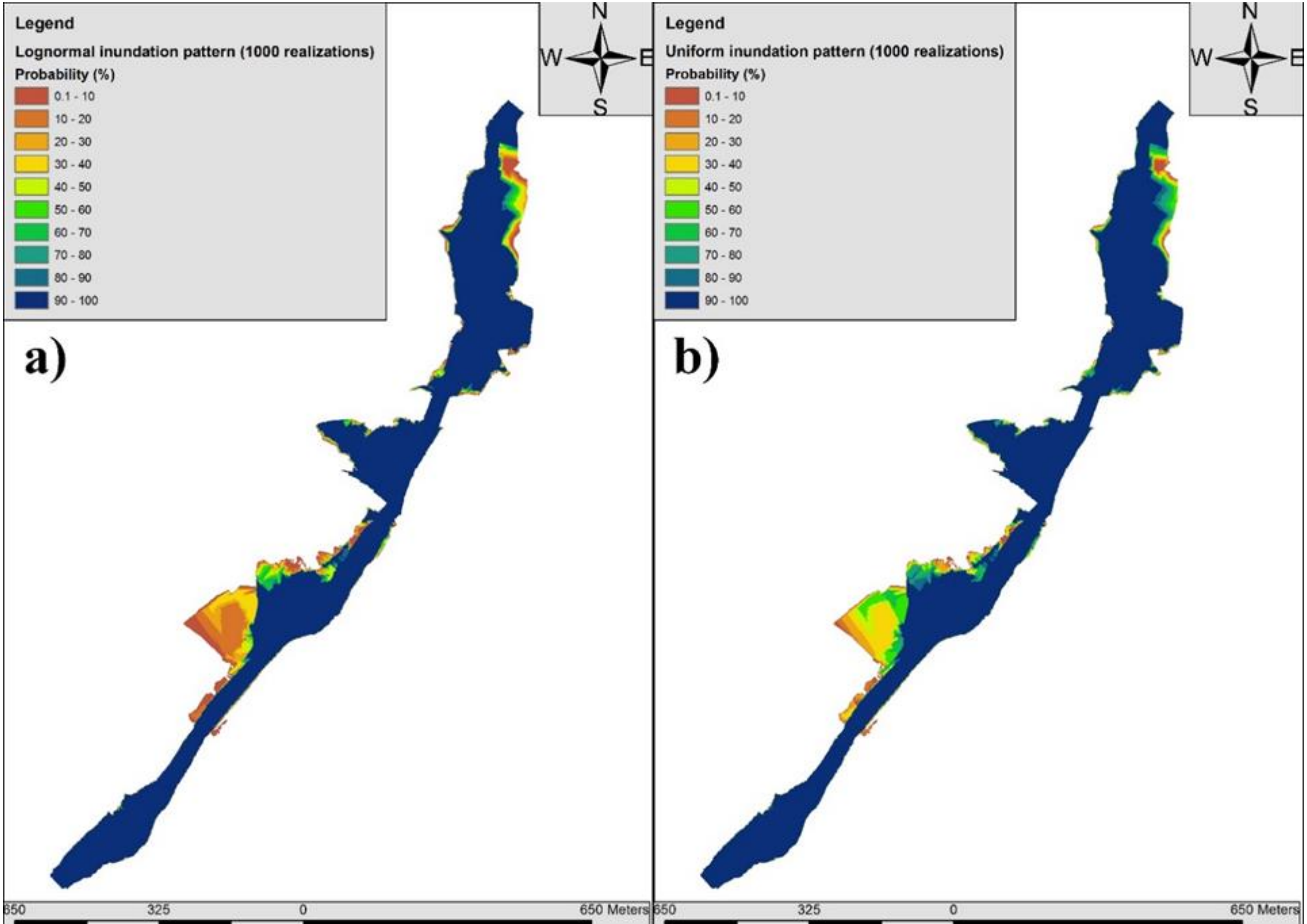
# Results




Papaioannou et al., 2017c

# Results

| MdAPE threshold level differences (%) | 18 | 20 | 22 |
|---|---|---|---|
| 18 | 0 | | |
| 20 | 11.73 | 0 | |
| 22 | 15.06 | 10.69 | 0 |

Flood inundation probabilities classes (%) of all threshold value of MdAPE statistical criterion

| Flood inundation probabilities classes (%) \ MdAPE threshold level | MdAPE 18% | MdAPE 20% | MdAPE 22% |
|---|---|---|---|
| **100-90** | 85.02 | 78.87 | 75.13 |
| **90-80** | 0.81 | 0.98 | 0.88 |
| **80-70** | 0.86 | 0.84 | 1.01 |
| **70-60** | 1.02 | 1.23 | 1.35 |
| **60-50** | 1.32 | 1.38 | 1.44 |
| **50-40** | 1.89 | 1.65 | 1.64 |
| **40-30** | 1.39 | 2.72 | 2.53 |
| **30-20** | 1.74 | 2.72 | 3.82 |
| **20-10** | 3.74 | 5.06 | 6.02 |
| **10-0** | 2.20 | 4.56 | 6.18 |

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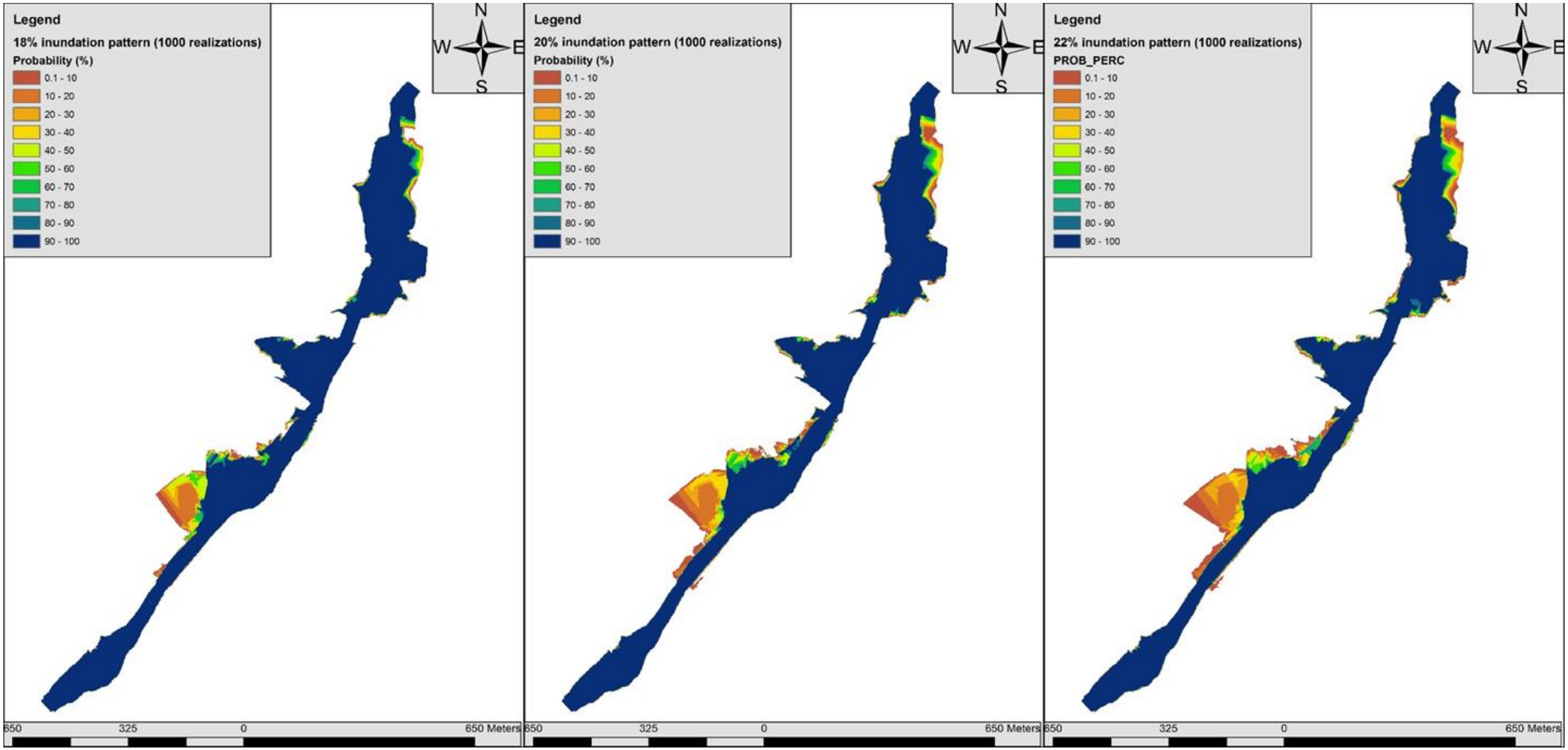
ΔΗΜΟΚΡΙΤΕΙΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΘΡΑΚΗΣ

# Results

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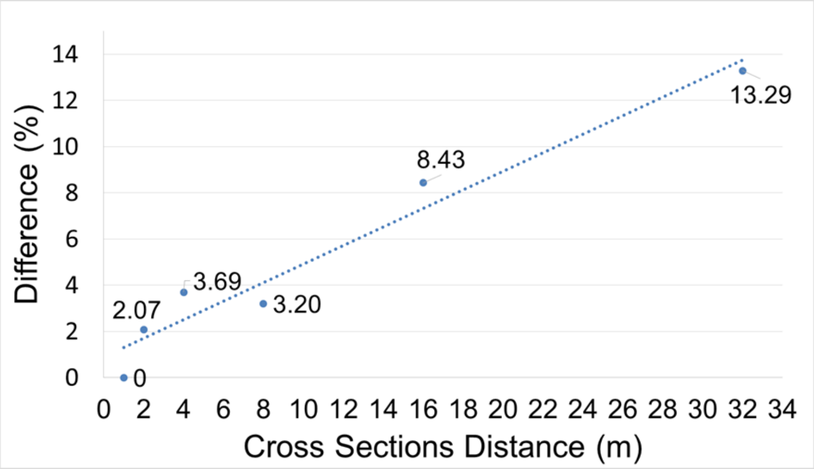
# Results




Flood inundation probabilities classes (%) of all cross section distance intervals.

| Flood inundation probabilities classes (%) \ Cross Sections Distance interval | 1m | 2m | 4m | 8m | 16m | 32m |
|---|---|---|---|---|---|---|
| **100-90** | 78.87 | 79.08 | 80.31 | 79.02 | 80.04 | 80.77 |
| **90-80** | 0.98 | 1.02 | 0.96 | 0.97 | 0.95 | 0.84 |
| **80-70** | 0.84 | 0.92 | 0.82 | 0.87 | 1.12 | 1.08 |
| **70-60** | 1.23 | 1.18 | 1.21 | 1.26 | 1.06 | 1.08 |
| **60-50** | 1.38 | 1.38 | 1.25 | 1.21 | 1.46 | 1.40 |
| **50-40** | 1.65 | 1.56 | 1.51 | 1.58 | 1.83 | 2.01 |
| **40-30** | 2.72 | 2.75 | 2.37 | 2.87 | 2.99 | 2.69 |
| **30-20** | 2.72 | 2.77 | 2.95 | 2.59 | 2.64 | 4.30 |
| **20-10** | 5.06 | 4.97 | 4.93 | 5.27 | 4.56 | 2.53 |
| **10-0** | 4.56 | 4.39 | 3.70 | 4.35 | 3.35 | 3.31 |

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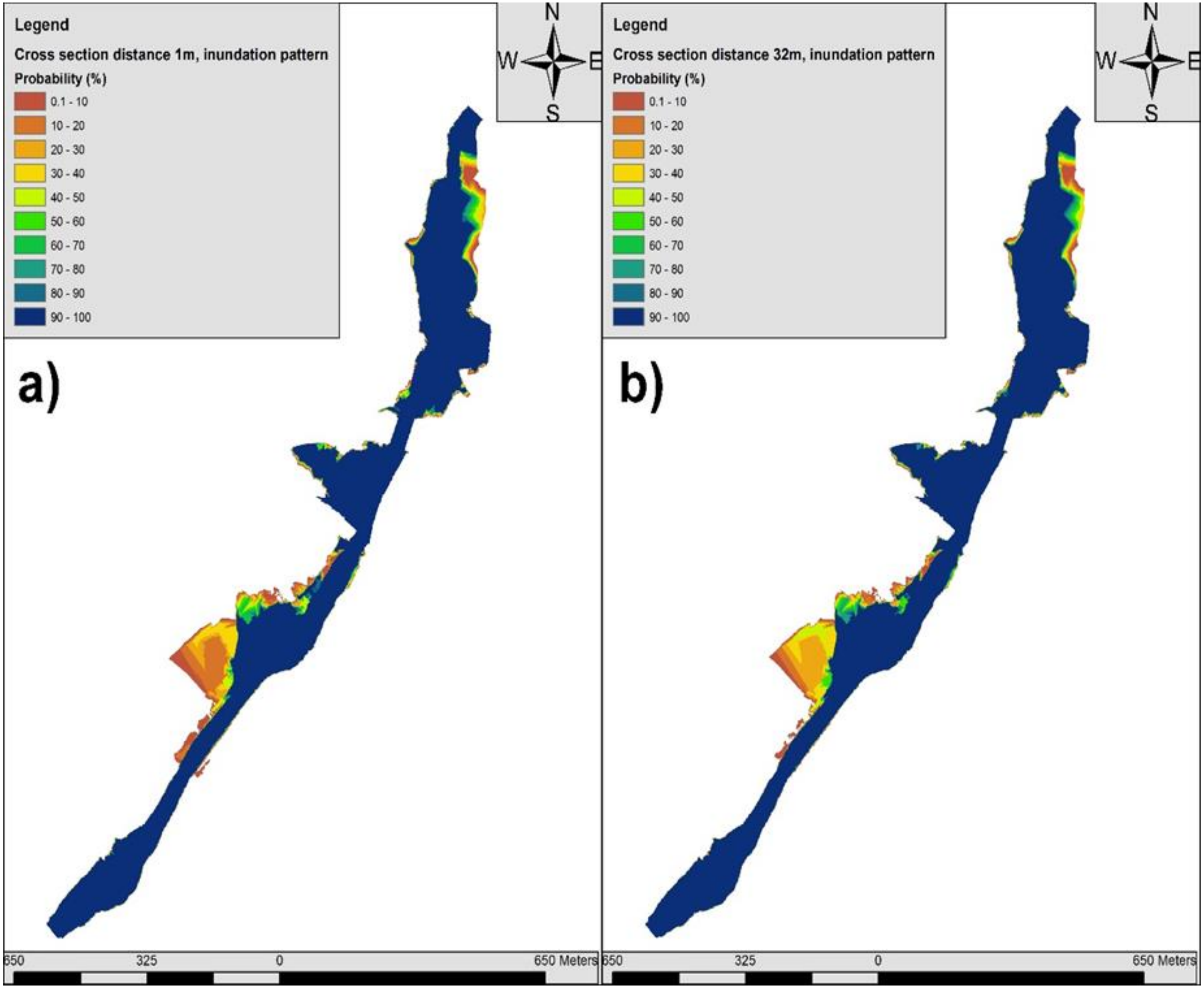
# Results

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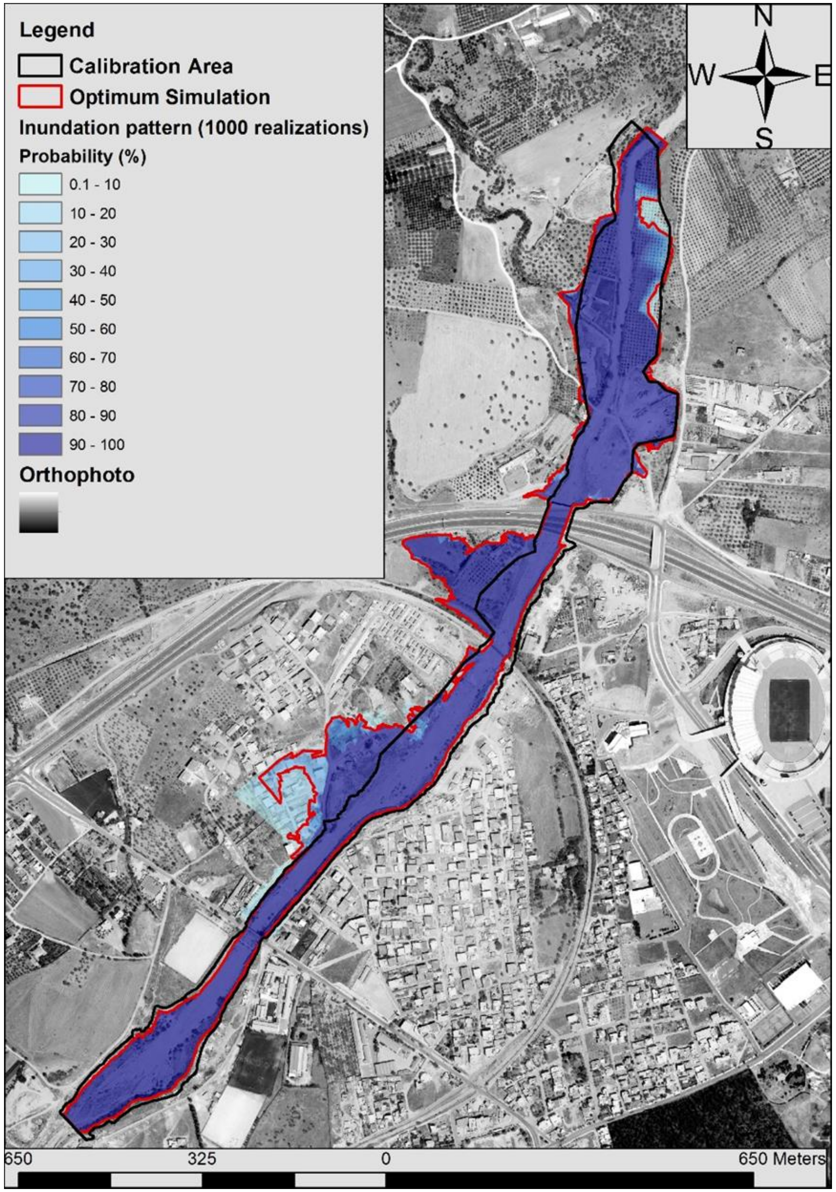
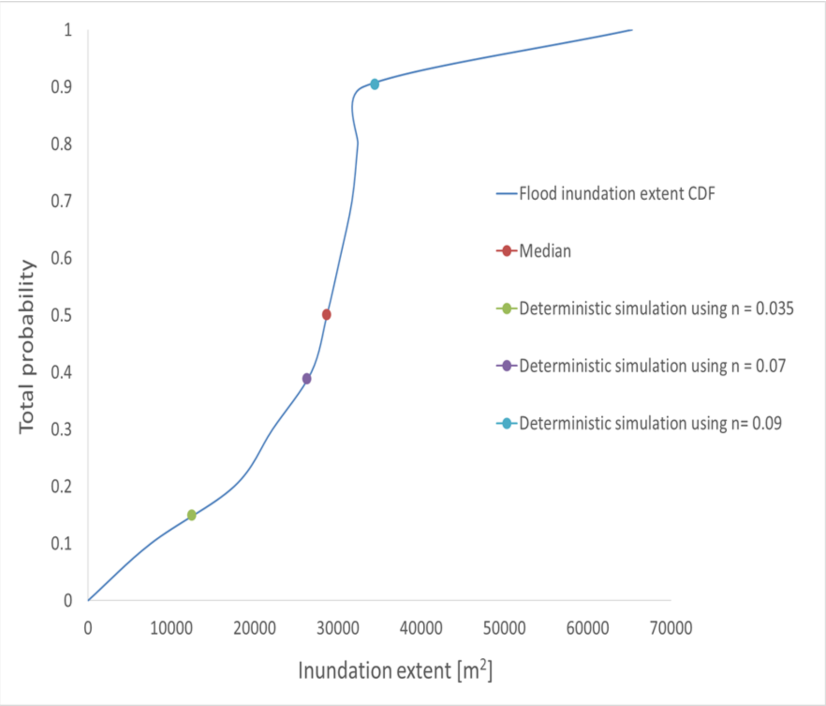
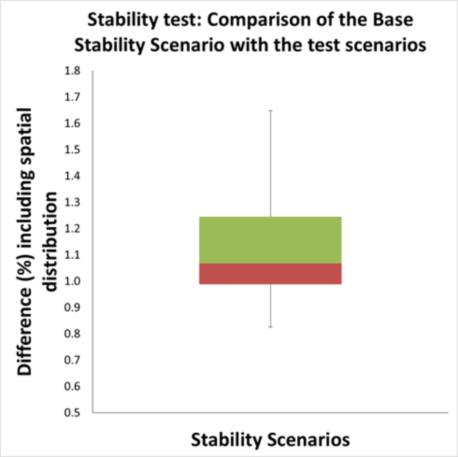
# Results




| Number of simulation | Differences with the Base scenario (%) |
|---|---|
| 1st | 1.25 |
| 2nd | 1.07 |
| 3rd | 1.65 |
| 4th | 0.82 |
| 5th | 0.99 |



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# Concluding Remarks

- A floodplain mapping uncertainty framework for ungauged streams - Complex riverine topography + Cobble and gravel bed materials.
- Limited data and information (only flood extent data).
- Optimum configuration of the Uncertainty analysis component :
  - lognormal distribution,
  - 1000 realizations,
  - 1 m spacing of the cross sections (up to 16 m),
  - the choice of the statistical criterion (MdAPE) and
  - the setup of threshold to 20%.
- Validation - Historical flood event.
- **Ungauged streams – Probabilistic Flood Maps (PFMs)**

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# Thank you for your attention