Responses to review comments

We deeply appreciate reviewers' valuable comments and kind suggestions. We have revised the manuscript accordingly and present responses to them in this sheet. The revised parts are colored in red in the following responses and the revised manuscript.

The main points:
1. The literature review is inadequate.
There are too few references on the relevant past work on surrogate modelling (also known as emulation or meta-modelling or response surface). Please cite several papers (say 5-6?) with various settings (e.g. parameters ranges of earthquakes/landslides sources or other uncertain parameters such as roughness, applications to faster than real time early warning or hazard assessments) for tsunami emulation. There are papers on this topic in NHESS and other journals in the last five years or so, I let the authors decide which ones to cite and comment on to contrast with their approach. Please discuss them a bit to help the reader situate your work. In particular, the mainstream method of Gaussian Process (GP) emulation to create surrogates is powerful as it provides uncertainties and allows for high nonlinearities, so must be mentioned and discussed, as these generalise in some way equation (17) in this paper.
Remove the sentence and references "LeVeque et al. (2016) and Melgar et al. (2016) utilize the Karhunen–Loève expansion to consider the distribution of slips on a fault under various scenarios" as these are irrelevant here and the sentence is out of place.
The other references are relevant and fine to keep.

As the reviewer pointed out, the explanations of past studies on surrogate modeling may have not been enough. Thus, we have added the explanations in the introduction to clarify the difference from them. Since the RBF interpolation is regarded as a Gaussian Process emulation, we have added this point in the manuscript. In addition, we have removed the sentence "LeVeque et al. (2016) and Melgar et al. (2016) utilize the Karhunen–Loève expansion to consider the distribution of slips on a fault under various scenarios", because it was irrelevant to this part, as you pointed out.

【Original manuscript, Page 2, Line 40-43】
Therefore, a surrogate modeling-based prediction method is employed in this study. However, since this study considers multiple evaluation points to determine tsunami force, the methods employed in Fukutani et al. (2019) and Kotani et al. (2020), which require surrogate models to be defined at each evaluation point, are inefficient. To overcome this problem, a mode decomposition technique is used to construct surrogate models.

【Revised manuscript, Page 2, Line 41-48】

Therefore, a surrogate modeling-based prediction method is employed in this study. Surrogate modeling has been widely accepted for uncertainty quantification and probabilistic risk assessment, such as studies using Response Surface (e.g., Fukutani et al., 2019; Kotani et al., 2020), Gaussian Process (e.g., Sarri et al., 2012; Salmanidou et al., 2017, 2021), Polynomial Chaos Expansion (e.g., Denamiel et al., 2019; Giraldi et al., 2017; Sraj et al., 2017), and Multifidelity Sparse Grids (e.g., de Baar and Roberts, 2017). These works demonstrate the potential of the Surrogate modeling-based approach, while the surrogate model considering spatio-temporal variation has not been well studied. Since this study considers time variation of spatial distribution of tsunami risk, a mode decomposition technique is efficiently used to construct surrogate models.

【Original manuscript, Page 7, Line 169-170】

In this study, $f_k(\beta)$ is determined by the interpolation with radial basis functions (RBF) (Buhmann, 1990) because it is applicable even if the parameters are not distributed in equidistant intervals and even if some defects are present in the data.

【Revised manuscript, Page 7, Line 172-174】

In this study, $f_k(\beta)$ is determined by the interpolation with radial basis functions (RBF) interpolation (Buhmann, 1990) which is regarded as a Gaussian Process (GP) regression. The GP regression is applicable even if the parameters are not distributed in equidistant intervals and even if some defects and high non-linearity are present in the data.

【Original manuscript, Page 2, Line 47-48】

LeVeque et al. (2016) and Melgar et al. (2016) utilize the Karhunen–Loève expansion to consider the distribution of slips on a fault under various scenarios.

【Revised manuscript】

(Removed)

2. Section 2.3 needs a bit of clarification. line 167 should be "input parameters beta:". The error in equation (18) is not mentioned, but it is present as it is a regression equation and should be in the

equation. Line 1801-182 more details are needed on what cross-validation is used, why a Bayesian optimisation if used and how.

As the reviewer pointed out, $f_k(\boldsymbol{\beta})$in line 167 was a mistake, we have fixed it in the manuscript.

【Original manuscript, Page 7, Line 166-167】

Then, the surrogate model can be expressed in the following equation whose independent variables are input parameters $f_k(\boldsymbol{\beta})$:

【Revised manuscript, Page 7, Line 169-170】

Then, the surrogate model can be expressed in the following equation whose independent variables are input parameters $\boldsymbol{\beta}$:

Because the explanation of regression was insufficient, we have added an explanation including the regression equation. In addition, since there were no detailed explanations of cross-validation and Bayesian optimization in the manuscript, we have added their explanations.

【Original manuscript, Page 8, Line 178-182】

In this study, ridge regression (Hoerl and Kennard, 1970) is used to compute weights for Eq. (18). By introducing the ridge regression, it is possible to prevent the overfitting problem. Since the accuracy of the interpolation depends on the regularization parameter used in the ridge regression and the smoothness parameter of the RBF interpolation, these values are determined by the application of a certain cross-validation technique (Stone, 1974) combined with the Bayesian optimization (Mockus, 1975) in this study.

【Revised manuscript, Page 8, Line 182-190】

In this study, ridge regression (Hoerl and Kennard, 1970) is used to compute weights for Eq. (18). The weights are obtained by solving the following optimization problem:

$$\arg\min_{\mathbf{w}_k}\left(||\boldsymbol{\alpha}_k - \boldsymbol{\Phi}\mathbf{w}_k||_2^2 + \lambda||\mathbf{w}_k||_2^2\right) \quad (k = 1, \dots, r) \tag{19}$$

where λ is the regularization parameter, $\boldsymbol{\alpha}_k$ is the vector of coefficients for the k-th mode, $\boldsymbol{w}_k$ is the vector of weights for the k-th mode, and $\boldsymbol{\Phi}$ is the coefficient matrix in equation (18). By introducing the ridge regression, it is possible to prevent the overfitting problem. Since the accuracy of the interpolation depends on the regularization parameter λ and the smoothness parameter γ of the RBF interpolation, these values are determined by the application of a certain cross-validation technique (Stone, 1974). In this study, the 4-folded cross-validation is applied to determine the parameters γ and λ, and the Bayesian optimization (Mockus, 1975) is used to efficiently search for the optimal values of γ and λ in the parameter space.

3. Table 1 and 4. Conclusion: The design used is a grid, which is much less efficient than Latin Hybercubes or sequential designs for GP emulation, or sparse designs for Polynomial Chaos surrogates: nobody uses a grid anymore to construct emulators. A reference to more efficient methods, ideally in tsunami emulation/surrogate context is needed. The study would have greatly benefited from a better design using the same computational budget.

This study mainly presents the framework of the surrogate model using the mode decomposition technique and does not focus on the sampling of simulation scenarios. However, as the reviewer suggested, Gaussian Process, Polynomial Chaos, and other sampling methods can also be applied in the framework, and combining with such methods can probably improve accuracy of the surrogate model. In order to mention this point, we have added an explanation in the conclusion.

【Original manuscript, Page 27, Line 368-369】
However, when increasing the types of input parameters, as the number of scenarios that need to be considered is immense, it is important to use an efficient method such as parameter sampling (McKay (1979)) for setting the scenarios.

【Revised manuscript, Page 28, Line 381-383】
However, when increasing the types of input parameters, as the number of scenarios that need to be considered becomes immense, it is pertinent to use efficient methods for parameter sampling such as Latin Hypercubes (McKay (1979)), etc.

4. Performance is explored on the 10 cases of +_10 deg rake. This are quite central so may not represent the whole range of inadequacies of the surrogate. Usually a leave-one-out diagnostic is performed and would not cost much here as there is no need for any more simulation. It would show a better picture than this narrow set of scenarios that might be rather easy to predict.

As the reviewer pointed out, there is room for more detailed validation. However, the main objective of this study is to propose a framework for rapid tsunami force prediction. We believe that the present surrogate models have enough performance for the purpose of demonstrating the effectiveness of the framework. Because the accuracy of the surrogate models should be discussed in conjunction with the sophistication of parametric sampling, it would be helpful if we could make this as one of the future works. We ask for the reviewer's understanding.

5. Please discuss more the sometimes 50% differences between model and surrogate outputs in fig 18-19: these could be very local aspects of topography that cannot be captured by a global POD approach that assesses the overall variability. This is one major deficiency in this application, so needs to be acknowledged. Please check the relative errors of 400% as they do not seem to match the figures: these should be around 50% max.

As the reviewer pointed out, the large error reflects the local aspects of topography and is an important point we should notice. Therefore, we have added an explanation to clarify the point. Also, in response to this point reviewer raised, we have checked again the large relative error using the mean value and then found that the calculation was incorrect. Accordingly, we have revised the relative errors in Table 2 and in the manuscript.

【Original manuscript, Page 25, Line 328-333】

Here, it is confirmed that it is possible to represent the simulation results using arbitrary parameters with the surrogate model. In specific terms, the error rate is calculated. For each of the physical quantities, the root mean squared error (RMSE) for the time-series data of all points are calculated by using Eq. (21). The results are shown as follows in Table 2.

With regard to Table 2, the relative error to the mean value of time series data for a specific scenario was 434% for the impact force data and 414% for the water depth data in S2R3 and318%for the impact force data and252%for the water depth data in S5R7.

【Revised manuscript, Page 27, Line 337-346】

Here, it is confirmed that it is possible to represent the simulation results using arbitrary parameters with the surrogate model. However, as shown in Figs. 18 and 19, it should be noted that the surrogate model does not fully represent the local spatial distribution. More advanced mode decomposition techniques, such as the sparse modeling, are needed to improve the accuracy.

Next, the root-mean-squared error (RMSE) for the time-series data at all points are calculated for each of the physical quantities by using Eq. (22). The relative errors to the mean value and the maximum value are presented in Table 2. Here, "Mean value" is a root-mean-square of the corresponding quantity.

With regard to Table 2, the relative error to the mean value of time series data for a specific scenario was 37.2% for the impact force data and 45.1% for the water depth data in S2R3 and 32.4% for the impact force data and 36.7% for the water depth data in S5R7.

【Original manuscript, Page 26, Table 2】

Case name	S2R3		S5R7	
	Impact force	Inundation	Impact force	Inundation
Error (RMSE)	6.69×10^4 [N]	0.326 [m]	8.40×10^4 [N]	0.404 [m]
Mean value	1.54×10^4 [N]	0.0787 [m]	2.64×10^4 [N]	0.160 [m]
(RMSE)/(Mean value)	434 [%]	414 [%]	318 [%]	252 [%]
Maximum value	8.59×10^6 [N]	15.1 [m]	1.08×10^7 [N]	19.8 [m]
(RMSE)/(Mean value)	0.78 [%]	2.15 [%]	0.78 [%]	2.04 [%]

【Revised manuscript, Page 27, Table 2】

Case name	S2R3		S5R7	
	Impact force	Inundation	Impact force	Inundation
Error (RMSE, Equation (22))	6.69×10^4 [N]	0.326 [m]	8.40×10^4 [N]	0.404 [m]
Mean value	1.80×10^5 [N]	0.722 [m]	2.59×10^5 [N]	1.10 [m]
(RMSE)/(Mean value)	37.2 [%]	45.1 [%]	32.4 [%]	36.7 [%]
Maximum value	8.59×10^6 [N]	15.1 [m]	1.08×10^7 [N]	19.8 [m]
(RMSE)/(Maximum value)	0.78 [%]	2.15 [%]	0.78 [%]	2.04 [%]

Minor points:

1. how do you extract spatial modes in Fig 11 across times and temporal modes in line 274? A bit more clarity about the role of time is needed in the text.

As shown in Equation 20, all spatial distributions obtained in the simulation are included in the data matrix. This means that the spatial modes are common to all time and all scenarios. Temporal effects are expressed only by the coefficients. To make the explanation clearer, we have added an explanation.

【Original manuscript, Page 16, Line 274-275】

By applying proper orthogonal decomposition to this matrix, it is possible to extract a common temporal mode for data including time, and it is possible to construct a surrogate model including the time direction.

【Revised manuscript, Page 17, Line 282-284】

By applying proper orthogonal decomposition to this matrix, it is possible to extract a common temporal mode for data including time. Temporal effects are expressed by the coefficients of the modes, and it is possible to construct a surrogate model including the time direction.

Other revision

Because an article that should be cited in this manuscript was published during the peer review period, we have newly cited it in Introduction.

【Original manuscript, Page 2, Line 34-37】

Among these is a study on making real-time predictions using source information and precomputed tsunami waveform and inundation databases (Gusman et al., 2014), another uses a combination of precomputed tsunami databases and the neural networks (Fauzi and Mizutani, 2019), and another features the surrogate modeling of numerical simulation results (e.g., Fukutani et al., 2019; Kotani et al., 2020).

【Revised manuscript, Page 2, Line 34-38】

Among these is a study on making real-time predictions using source information and precomputed tsunami waveform and inundation databases (Gusman et al., 2014), another uses a combination of precomputed tsunami databases and the neural networks (Fauzi and Mizutani, 2019; Liu et al., 2021), and another features the surrogate modeling of numerical simulation results (e.g., Fukutani et al., 2019; Kotani et al., 2020).