Uncertainty in Kinematic Tsunami and Earthquake Source Inversion

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The beginning of the 21st century has seen a remarkable spate of large earthquakes, each generating observational data of a quality and coverage far exceeding what was available in the 20th century. The use of such data to infer earthquake source properties is now so routine that several kinematic rupture models are typically published very soon after a large earthquake's occurrence. Despite the importance of such models for understanding the generation of damaging ground motions and tsunamis, it can be argued that advances in methods for inferring rupture models from the data have not kept pace with the observations. Rupture models are typically inferred using least squares optimization, which makes it difficult to appraise both uncertainty and bias introduced by regularization and other ad hoc assumptions like maximum rupture velocity.

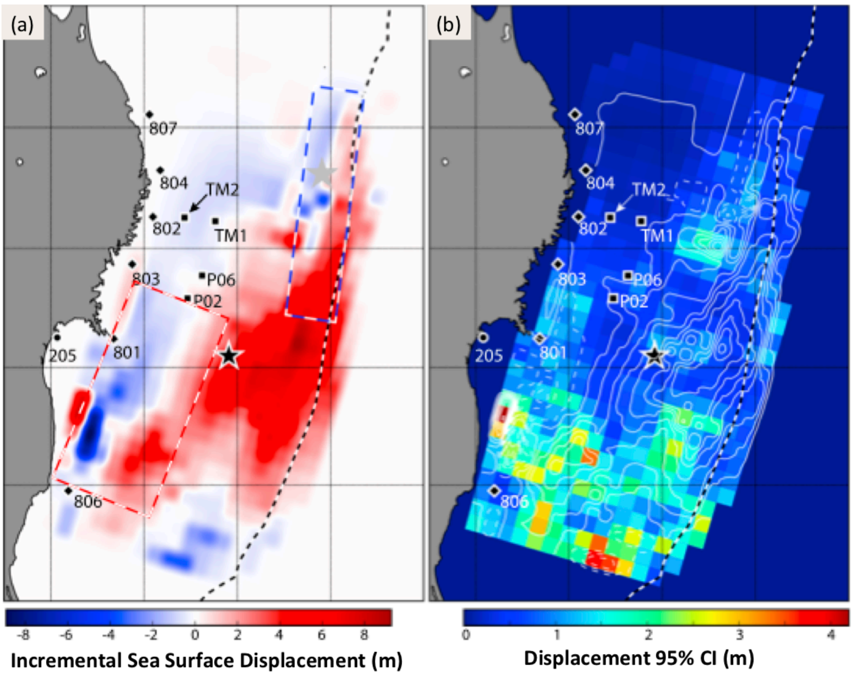

Figure 1. Inversion of the sea surface source for the 2011 Tohoku Tsunami. (a) the posterior median sea surface displacement and (b) the width of 95% credibility intervals. Lower uncertainty in the northern part of the source region reflects better sensor coverage there. From Dettmer et al. [2015].

In this presentation we will discuss recent progress in the development of Bayesian methods for inferring kinematic models of earthquake and tsunami sources that allow for assessment of uncertainty. We will present one approach to the classical finite fault inversion method that allows a rigorous appraisal of uncertainty with only a modest increase in computational cost over traditional least squares optimization, as well as a much more sophisticated approach that provides rigorous uncertainty appraisal and accounts for the influence of model selection (i.e., fault discretization) on the inversion results. The latter approach, known as Trans-dimensional Bayesian inversion, does not require regularization, instead allowing results to locally adapt to source complexity, but in "parsimonious" way that favors the simplest models consistent with the information in the data.