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Uncertainty quantification and reliability assessment in operational oil spill forecast modeling system

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ABSTRACT

As oil transport increasing in the Texas bays, greater risks of ship collisions will become a challenge, yielding oil spill accidents as a consequence. To minimize the ecological damage and optimize rapid response, emergency managers need to be informed with how fast and where oil will spread as soon as possible after a spill. The state-of-the-art operational oil spill forecast modeling system improves the oil spill response into a new stage. However uncertainty due to predicted data inputs often elicits compromise on the reliability of the forecast result, leading to misdirection in contingency planning. Thus understanding the forecast uncertainty and reliability become significant. In this paper, Monte Carlo simulation is implemented to provide parameters to generate forecast probability maps. The oil spill forecast uncertainty is thus quantified by comparing the forecast probability map and the associated hindcast simulation. A HyosPy-based simple statistic model is developed to assess the reliability of an oil spill forecast in term of belief degree. The technologies developed in this study create a prototype for uncertainty and reliability analysis in numerical oil spill forecast modeling system, providing emergency managers to improve the capability of real time operational oil spill response and impact assessment.

1. Introduction

When an oil spill occurs at late night in heavily trafficked shipping channels, operational oil spill forecast modeling system provides the spill transport predictions needed for rapidly deploying emergency responses equipment, e.g. booms, dispersant, or skimmer boats. As moving equipment around the margins of an estuary or bay can be time consuming, information on the uncertainty of the forecast spill path could be insightful in deciding whether equipment should be immediately committed or moved to a central location (relative to possible spill paths) to await predictions with greater confidence. Unfortunately, such data is not generally available from existing operational oil spill modeling systems.

1.1. Uncertainty in oil spill modeling

The cause of oil spill forecast uncertainty ranges from the modeling system itself to the forecast model inputs. At the system limit are the interdisciplinary sub-models including chemistry, turbulence, hydrodynamics, meteorology, and hydrology - providing a 2D or 3D oil spill forecast trajectory (You and Leyffer, 2011; Zelenke et al., 2012; Mackay et al., 1980; Huang, 1983; ASA, 1997; Reed, 2000). Although some previous studies (e.g. Price et al., 2004; Elliott and Jones, 2000; Reinaldo and Henry, 1999) proved that numerical formulations would have influence on the performance of oil spill modeling, the forecast uncertainty in this end has been reduced significantly as the evolution of the state-of-the-art models and parallel computing power. At the forecast inputs limit are weather and hydrodynamic forecast time series (e.g. wind and tidal force) required by the oil spill modeling. Presently weather forecasts have qualified predictive capabilities for periods up to 4 days, but it becomes more and more unstable as time progresses (Sebastiao and Soares, 2007; Sebastiao and Soares, 2006). The forecast data derived from operational models, such as Texas coastal wind forecasts from the National Centers for Environmental Prediction (NCEP) Eta model (NECP, 2015), might have poorer predictive skills for an even shorter forecast period. Unlike the uncertainty from the modeling system limit, the uncertainty from forecast data is inevitable.

NOAA's GNOME (General NOAA Operational Modeling Environment) oil spill transport model developed its oil spill forecast uncertainty assessment package by undertaking self-made assumptions, i.e. modelers should have to guess what the uncertainties of inputs are. The key is to perturb different movers by slightly changing the magnitude or the direction of winds and currents input vectors (Zelenke et

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al., 2012). The Oil Spill Risk Analysis (OSRA) model estimates the oil spill forecast uncertainty by generating an ensemble of oil spill trajectories over many years of hydrodynamic and meteorological input fields. The forecast uncertainty is assessed by analyzing the difference of the simulated spills under the assumption that the occurrence rates of the spills and the inputs will probably like those that might happen in the future (Price et al., 2003). Drifter modeling along with statistical post-processing is also a practical approach to estimate the forecast uncertainty in most recent studies (Sebastiao and Soares, 2006; Price et al., 2006). Many of these methods advocate a minimum regret strategy to deliver the predicted data to the oil spill modeling system (Galt, 1997; Galt and Payton, 1999). However, all of these methods do not provide explicit information of what can go wrong and how much is it to go wrong, of which are relatively more important issues in operational oil spill forecast modeling. Hence more elaborate analysis is required to quantify the oil spill forecast uncertainty so that oil spill managers could have a general idea of the forecast quality.

1.2. Reliability of oil spill forecast

Uncertainty in forecast modeling is pervasive; however in most operational engineering, economics, and nature science fields, numerical simulations based on forecast data are the only sources for decision making before hindcast or observed data is available, especially for issues that rapid response is critical. As to oil spill accidents, the observed data is always rare when a spill occurs. The realization of forecast uncertainty in operational oil spill modeling system draws concerns for oil spill managers, who pay high attention to the reliability of the forecast results. Thus, facing to the forecast results of an oil spill modeling, oil spill managers would always ask: how likely is it to go wrong? Or how much can I trust it? This is another uncertainty issue that pertains to the confidence or reliability of a numerical oil spill forecast.

Reliability is the most important forecast quality that measures the degree of the likelihood that a forecast captures the actual event being predicted. Reliability assessment generally involves ensemble forecast, because real physics can only provide a single outcome for a particular forecast, which is impossible to form a probabilistic representation of reliability (Tippett et al., 2014). There are many ways of quantifying forecast reliability. Brown et al. (1997) assessed the reliability of the power distribution system to momentary interruptions and storms by using Monte Carlo simulation. Weisheimer and Palmer (2014) and Ho et al. (2013) analyzed the reliability of seasonal climate forecasts based on reliability diagrams which are tools to visualize and quantify the statistical reliability of a forecast system. Winkler et al. (2010) examined the reliability of power system during hurricanes via network topology. There are few studies concentrating on the reliability of oil spill modeling (e.g. Abascal et al., 2010; Wang and Zhou, 2009), however, these studies aim at specific model or spill event, which simply cannot be applied over a broader sense. A more general approach is required for present operational oil spill forecast modeling where the state-of-the-art numerical models and forecast data sources are changing all the time.

This paper defines several new terms to quantify forecast uncertainty in operational oil spill modeling system. Monte Carlo simulation is applied to evaluate forecast errors so that multiple pseudo-forecast series can be generated to form a time-evolution of forecast probability map for uncertainty quantification. The Hydrodynamic and Oil Spill Python (HyosPy) (Hou and Hodges, 2014; Hou et al., 2015; Hodges et al., 2015) is exploited to assess forecast reliability of oil spill predictions in a more general sense.

2. Methods

2.1. Forecast uncertainty probability map (FUPM)

Oil spill forecast uncertainty has two facets - temporal and spatial. Temporal uncertainty originates from the arrival time discrepancy of the surface oil at a specific location (e.g. Abascal et al., 2010); spatial uncertainty emerges from the potential transport track of the spill (e.g. Nelson et al., 2015 for large scale oil spill spatial uncertainty analysis; Sebastiao and Soares, 2006 analyzed smaller cases in a coastal zone via an oil spill model).

From an operational response perspective, the critical question within a bay or estuary is *when and where will the spill hit the shoreline?* The *hit time* can be defined as the time that a forecast predicts the spill to hit a particular stretch of beach and the hit location as the location of beaching. For a given forecast period (T), not all spills will hit the shoreline, so it is also useful to consider a simply binary discriminator of *beaching/no beaching*. The forecast uncertainty can be divided into four categories, that we will quantify as metrics:

1. *Hit time uncertainty* – U_t: the deviation of the transport time between the hindcast and forecast when one or both of them are beaching.
2. *Hit location uncertainty* – U_l: the deviation of possible or simulated-definite landing positions between the hindcast and forecast when one or both of them are beaching.
3. *Transport area uncertainty* – U_a: the deviation of transport directions (represented by area for ease of calculation) between the hindcast and forecast.
4. *Transport speed uncertainty* – U_s: the deviation of transport speed between the hindcast and forecast.

Quantifying the above metrics requires assessing the difference between observations and the ensemble of possible forecasts, i.e. a forecast probability map. These metrics could be developed/used in three different ways: (1) as an a priori exercise with field drifter data as observations to evaluate likely uncertainty in models; (2) as an operational task during a spill, where the latest spill observations are used to rapidly assess evolving uncertainty; or (3) as a model-model comparison where hindcast data driving the model represents the observations, and a range of forecast data driving the model provides the ensemble. The present work demonstrates the technique using the model-model approach, as we do not have access to a data set of drifters or observed oil spill evolution.

The forecast probability map is composed of multiple possible forecasts in the same simulation period. However, a single simulation period could have only one forecast, hence pseudo-forecast need to be created. In this work, the pseudoforecast is developed by identifying input forecast error (ε_k) based on Monte Carlo simulation. Specifically,

$$\varepsilon_k = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(f_{ik}-h_{ik}\right)^2} \tag{1}$$

where k denotes input class (i.e. wind, tide, river flow); f_{ik} is the input forecast time series; h_{ik} is the input hindcast time series; $i = 1, 2, \ldots N$; N is the number of records within the input time series.

The probability density function of ε_k, that is PDF(ε_k), is obtained by applying Monte Carlo simulation on ε_k based on multiple sets of input forecast/hindcast time series in different T. Thus, the pseudo-forecast

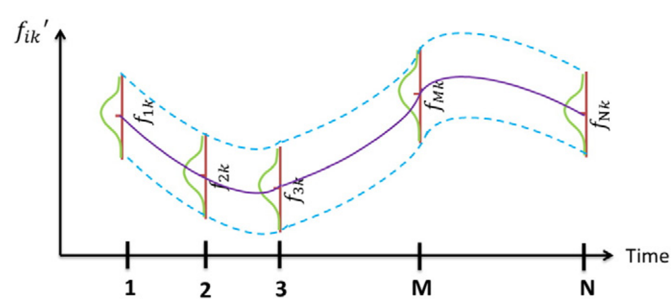

Fig. 1. Pseudo-forecast time series generation mechanism.