Adopting Model Uncertainties for Tropical Cyclone Intensity Prediction

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ABSTRACT

Quantifying and reducing the uncertainty of model parameterizations using observations is evaluated for tropical cyclone (TC) intensity prediction. This is accomplished using a nonlinear inverse modeling technique that produces a joint probability density function (PDF) for a set of parameters. The dependence of estimated parameter values and associated uncertainty on two types of observable quantities is analyzed using an axisymmetric hurricane model. When the observation is only the maximum tangential wind speed, the joint PDF of parameter estimates has large variance and is multimodal. When the full kinematic field within the inner core of the TC is used for the observations, however, the joint parameter estimates are well constrained. These results suggest that model parameterizations may not be optimized using the maximum wind speed. Instead, the optimization should be based on observations of the TC structure to improve the intensity forecasts.

1. Introduction

It is widely recognized that the skill of tropical cyclone (TC) track forecasts has improved considerably during the past decade, whereas the skill of intensity forecasts has not improved as much (e.g., Rappaport et al. 2009). Although multiple factors have been hypothesized to explain the lack of measurable improvement in TC intensity prediction, one of the main challenges is the uncertainty in parameterized representations of physical processes in numerical weather prediction models used for TC intensity (e.g., Rogers et al. 2006).

Recent studies have demonstrated large sensitivity of numerical TC intensity forecasts to the choice of model parameterizations (e.g., Braun and Tao 2000; Zhu and Zhang 2006; Li and Pu 2008; Pattnaik et al. 2011; Green and Zhang 2013). For example, Li and Pu (2008) found significant differences in the intensity and structure forecasts of a rapidly deepening hurricane due to differences in the storm structure resulting from various cloud microphysical and planetary boundary layer parameterizations. Similarly, Green and Zhang (2013) showed variations in TC intensity forecasts due to the use of different surface flux parameterizations in their numerical simulations. Although these and other studies have demonstrated a sensitivity of TC intensity to the choice of parameterization, it is difficult to ascertain which parameterizations (or parameter values within them) would be optimal for improving the accuracy of TC intensity forecasts. Among other factors, the difficulty arises from the lack of a formal measure of optimality for representing the uncertainties in the model parameterizations.

In this study, the estimation of parameter uncertainty is investigated using an optimal estimation approach. As an introductory experiment, we employ a simplified two-dimensional model and perform the estimation of parameter uncertainty using a nonlinear inverse modeling method. This paper proceeds as follows. The optimal estimation approach along with the experimental setup

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for the introductory study is briefly explained in the next section. Results obtained from using two different set of observable variables are discussed in section 3, followed by the conclusions of this study in section 4.

2. Method

a. Inverse estimation approach

This study employs the general stochastic inverse problem theory as introduced by Mosegaard and Tarantola (2002). Previous studies (Vukicevic and Posselt 2008; Vukicevic et al. 2010; Coddington et al. 2012) demonstrated the utility of this theoretical formulation in diagnostic analyses of nonlinear estimation problems with atmospheric models containing a small number of control parameters. The formulation allows for explicit computation of a joint posterior probability density function (PDF) of the parameters, given a nonlinear model and observations with their associated stochastic uncertainties. The posterior PDF is computed by conjunction of a numerically determined model-based PDF, in a joint space of parameter and observation values, with an observation-based PDF. The model-based PDF includes explicitly computed transfer functions between parameters and observation quantities, as well as a PDF representation of model solution with uncertainty in the observation space. This uncertainty reflects the presence of modeling errors that are not associated with the control parameters. The transfer function explicitly accounts for the variability due to these parameters. The method is diagnostic because testing the impact of different observable quantities and error characteristics of the model on the posterior PDF estimate of parameter values does not involve model integration other than the computation of the transfer functions. The numerical algorithm for computing the posterior PDF of parameter estimates based on this formulation is described in detail in Vukicevic and Posselt (2008).

In the current study the method is adapted for the estimation of parameter uncertainty using an axisymmetric hurricane model. The estimation is performed for two parameters within the parameterization of unresolved processes that are known to have significant impact on intensity prediction (described in the next section). Our goal is to evaluate the likelihood of joint parameter values simulating the observable quantities that are relevant to hurricane intensity, given the uncertainty in both the observations and model.

b. Experimental setup

The model employed in this study is the Axisymmetric Simplified Pseudoadiabatic Entropy Conserving Hurricane (ASPECH) model (Tang and Emanuel 2012). The variable-resolution grid stretching technique was used, with grid spacings of 4–8 and 0.5–0.8 km, in the radial and vertical directions, respectively, within a domain of 1000 km × 24 km. The model was initialized with an idealized vortex with a maximum surface tangential wind speed of 20 m s^{-1} and an environmental profile with 70% relative humidity and 29°C sea surface temperature. To ensure a robust representation of idealized hurricane evolution for the estimation of parameter uncertainty experiments, the model was first spun up for 48 h. The model state at 48 h was then used to initialize the simulations for computing the transfer functions and the reference "true" observations.

TABLE 1. Parameter values used in the true and simulated measurements. The true values were taken from the original setup of the ASPECH model as presented in Tang and Emanuel (2012).

Parameter	"True" value	Smallest bin	Largest bin
C_k	1.2×10^{-3}	0.6×10^{-3}	2.4×10^{-3}
L_{v_o} (J g^{-1})	2.678×10^6	2.0×10^6	3.0×10^6

The enthalpy exchange coefficient C_k and inflated latent heat of vaporization L_{v_o} parameters were chosen[1] for the estimation problem. The first parameter is known to influence TC intensity (e.g., Emanuel 1995), yet its reference value in the ASPECH model reflects a consensus of previous studies that have estimated this quantity (Tang and Emanuel 2012, and references therein). The second parameter was chosen because the model uses an inflated version of the latent heat of vaporization to compensate for the neglect of liquid-water entropy, as suggested by Bryan (2008). To compute the transfer functions, 30 discrete values for each parameter within the prescribed ranges were used (Table 1). Consequently, a total of $30^2 = 900$ simulations were produced, one for each possible combination of C_k and L_{v_o}. By doing this, we have assumed that all other parameters in the model are perfect, except for C_k and L_{v_o}. The reference true observations for the estimation were derived from the simulation with the parameter-value pair, as in the standard model configuration (see Table 1). It is important to note that the reference true observations are not real observations, but rather the model solution using the default values of C_k and L_{v_o}. The default pair of values was not used for the transfer-function ensemble.

The standard sensitivity result (i.e., time series of an intensity metric, which in this case is the maximum tangential wind speed) exhibits large sensitivity to varying

[1] Sensitivity tests done prior to employing the methodology showed a sufficient sensitivity of TC intensity to these two parameters, although the choice is somewhat arbitrary.

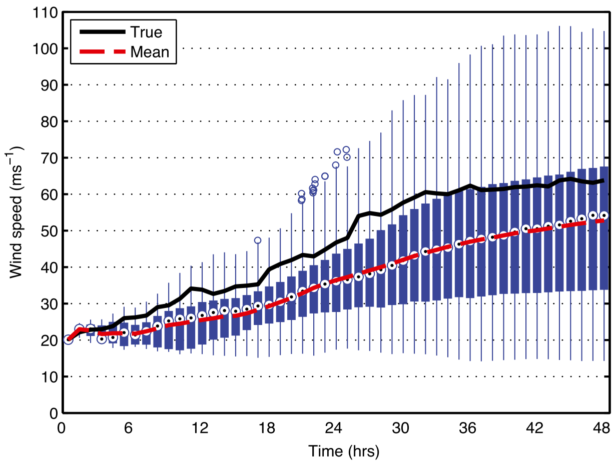

FIG. 1. Hourly maximum tangential wind speed for the reference "true" (black line) and the simulated measurements (box plots) resulting from all C_k and L_{v_o} combinations. For each boxplot the white circle depicts the median, the blue box marks the interquartile range (IQR), the whiskers extend up to 1.5 IQR, and the open blue circles are outliers. Also shown is the hourly mean from all simulated measurements (red line).

values of C_k and L_{v_o} (Fig. 1). Even though all cases start with the same tropical storm intensity, some cases strengthen substantially and others weaken throughout the forecast period. The variance of the ensemble, as well as the difference between the ensemble mean and the reference, increases with time. The deviation of the ensemble mean from the reference is large, suggesting that the response to parameter perturbations is nonlinear. In addition, many different combinations of parameters produce similar intensity. These properties imply that identifying a single optimal pair of parameters using the sensitivity results is unfeasible. Instead, an optimal subset of values should be determined. This is readily achievable by application of the optimal estimation method.

3. Optimal estimation results

The optimal estimates of joined values of C_k and L_{v_o} are analyzed for two types of observations of the axisymmetric hurricane winds: the maximum tangential wind speed ($v_{\max}$) and the total wind field (i.e., tangential, radial, and vertical wind) within the inner core of the simulated TC.

a. *Maximum wind speed observation*

We define the observation as $v_{\max}$ at a certain time. The transfer function for such observations is $v_{\max}$ as a function of paired parameter values for each selected time. The transfer function for 24- and 48-h observation times is displayed in Fig. 2. The values shown are the same as in Fig. 1 for the corresponding times, but now shown in the parameter space. Several properties of interest are evident: 1) small values of L_{v_o} correspond to low intensity irrespective of C_k; 2) for moderate to high values of L_{v_o} (above $2.75 \times 10^6\,\mathrm{J\,kg^{-1}}$) the intensity tends to increase with increasing L_{v_o}, but at a variable rate depending on the value of C_k; and 3) the change of intensity is not linear with respect to either L_{v_o} or C_k. Overall, consistent with the sensitivity result in Fig. 1, the transfer functions indicate that the impact of the parameters is mutually dependent and nonlinear. These properties were evident during other forecast times as well.

Using the transfer functions and estimates of observation and model errors, as outlined in the previous section, the joint posterior PDF of parameters is computed for each observation time. The errors associated with the observation of $v_{\max}$ are assumed Gaussian with a standard deviation of $\sigma_o = 5\,\mathrm{m\,s^{-1}}$. This value represents the expected uncertainty associated with the National Hurricane Center's operational estimates of TC intensity (Landsea and Franklin 2013). The model errors in the observation space are also assumed Gaussian. To estimate the standard deviation of the model PDF, several ASPECH simulations were used, but perturbing different physical variables in the initial conditions (e.g., relative humidity, maximum wind speed, etc.). As a result of this method, the model standard deviation was estimated to be $\sigma_m = 3.5\,\mathrm{m\,s^{-1}}$. This estimate represents the chaotic variability in the model due to small perturbations in the initial conditions, but not associated with L_{v_o} and C_k.

The joint posterior PDFs were computed for every 6-hourly forecast, but only the PDFs corresponding to the 24- and 48-h observation times will be discussed here as other times showed similar characteristics. As expected, Fig. 3 shows that these PDFs are similar in shape to the transfer functions within the range of parameter values that is determined by convolution of the observation and model PDFs in the observation space. This is consistent with the findings of Vukicevic and Posselt (2008). The posterior PDFs for both observation times exhibit multiple maxima and large variance for both parameters. The absolute maximum of each PDF is in the neighborhood of the reference true solution; however, because of the large variance and multimodality of the PDF its likelihood is small. The results suggest that the optimal values of the parameters cannot be uniquely estimated when using the values of $v_{\max}$ as the observable quantity. Consistent with the sensitivity studies, they point to the need to use an ensemble of model parameterizations for TC intensity prediction. These results also indicate that the ensemble should be based on the optimal estimation in order to include realistic ranges and

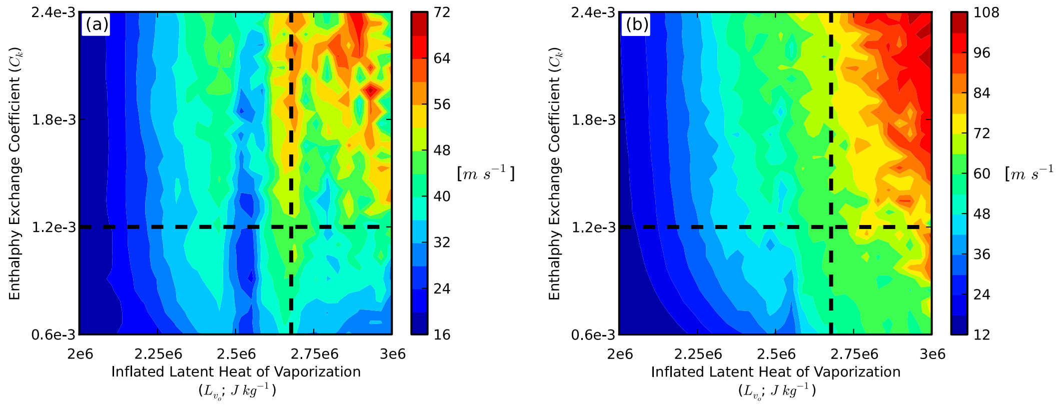

FIG. 2. Maximum tangential wind speed (color shaded; m s^{-1}) at (a) 24 and (b) 48 h for each two-parameter combination. The dashed lines correspond to the reference true values for each parameter; their intersection shows the maximum tangential wind speed for the control simulation.

mutually dependent parameter perturbations between different processes.

The impact of including multiple observation times in the posterior estimate is also evaluated. This impact is assessed in two ways: 1) by convolving the posterior PDFs for the individual observation times and 2) by computing the average of these PDFs. The convolution method is equivalent to performing the sequential estimation with cycling in time, whereas the average is equivalent to compositing the estimates that correspond to different periods of the TC vortex evolution. For both methods we used an observation frequency of 6 h, beginning with the 6-h forecast and ending with the 48-h forecast, inclusive. The convolution resulted in mutually independent estimates for the two parameters (Fig. 3c). The PDF corresponding to L_{v_o} is primarily bimodal, as in the individual observation times, but it exhibits less variance. The C_k PDF, however, is uniformly distributed, thus showing the high uncertainty associated with this parameter. On the other hand, the composite of the PDFs resulted in a weakly correlated joint parameter estimate with slightly better constrained maximum likelihood than for the individual observation times (Fig. 3d). With respect to the optimization of the ensemble of parameterizations, these results indicate that the ensemble estimates would be sensitive to the approach for combining information from different observation periods and cases.

b. *Kinematic field observations*

The possibility of estimating the parameters with respect to the observations of TC vortex wind field instead of just the maximum wind speed is explored next. The observations are defined as the radial u, tangential v, and vertical w wind within the inner 150-km radius, extending from the surface up to an 18-km height. Similar to the experiments for $v_{\max}$, the error variance for these observations is prescribed based on expected errors in practice (e.g., airborne measurements) and the variances for the model error in the equivalent fields were computed using ASPECH simulations with perturbed initial conditions.

Unlike for the maximum intensity experiment, the posterior solution shows perfect constraint with the kinematic field observations (i.e., the posterior PDF consists of a two-dimensional delta function for all observation times; Figs. 4a,b). The singular value estimates are close to, but not exactly equal to, the reference true values. This could be attributed to the low resolution of the parameter bins that was used to compute the transfer functions (i.e., only 30 bins were used for each parameter). Regardless of this limitation, the result suggests that parameterizations could be effectively optimized using the observations of kinematic structure of the TC vortex, which would, in turn, improve the simulations with respect to the maximum tangential wind speed.

Similar to the analysis for $v_{\max}$, the cumulative impact of observations from different times was evaluated for the kinematic field observations. To account for the lack of resolution of the parameter bins, the posterior delta-function PDFs were first smoothed by adding a two-dimensional uncorrelated Gaussian error to the posterior parameter estimate at each time independently. The convolution and averaging were then applied as in the previous section to compute the cumulative posterior PDFs. As in the $v_{\max}$ experiment, the convolution resulted in uncorrelated estimates for the two parameters but with a well-constrained maximum likelihood that is slightly biased relative to the reference true value (Fig. 4c). The compositing of the posterior PDFs produced correlated joint parameter estimates with a well-defined and more accurate maximum likelihood solution (Fig. 4d). It is worth noticing that the biases (the

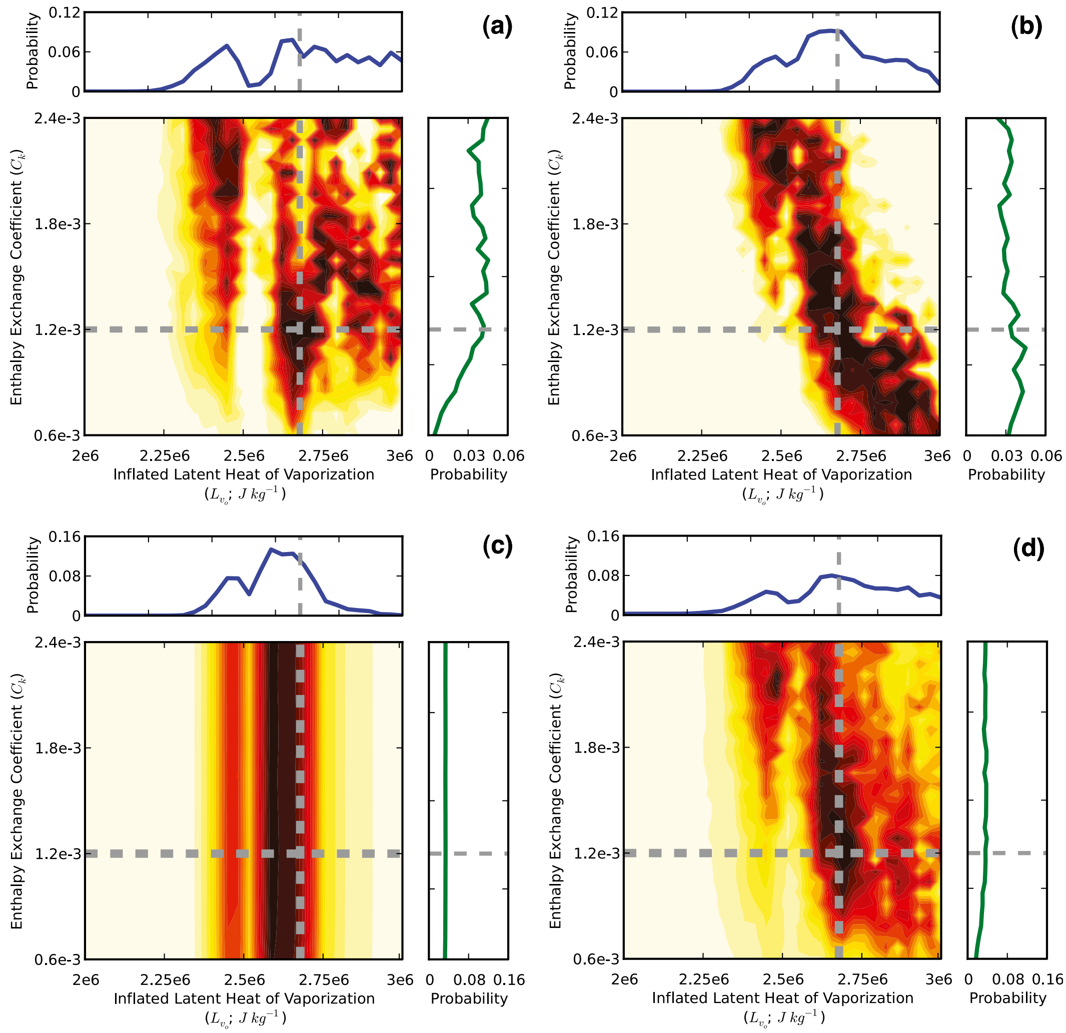

FIG. 3. Posterior joint PDFs in the parameter space (color shaded; darker colors represent relatively high probabilities) and marginal PDFs for C_k and L_{v_o} (green and blue lines, respectively). (top) The PDFs at (a) 24 and (b) 48 h. (bottom) The time-integrated PDFs, obtained by (c) convolving the 6-hourly PDFs and (d) averaging the PDFs over the 48-h simulation period. For all panels, the gray dashed lines depict the reference true parameter values, as in Fig. 2.

deviation from the reference solution) for the $v_{\max}$ and kinematic field experiments are very similar for the parameter L_{v_o}, and that for both experiments the biases are reduced when using the composited PDFs.

Additional experiments were carried out using only vertical profiles of u, v, and w at a specific distance from the storm center [e.g., at the radius of maximum wind (RMW), at 2 RMW, etc.] as observations. The PDFs from those experiments are surprisingly similar to those shown in Fig. 4, and also show a perfect constraint of the parameter values at all observation times (not shown).

4. Conclusions

The potential for quantifying and reducing uncertainty in parameterizations using optimal estimation with observations is evaluated for an idealized case of tropical cyclone intensity prediction. Using the nonlinear inverse estimation method with the Axisymmetric Simplified Pseudoadiabatic Entropy Conserving Hurricane model, it is shown that two parameters affecting the intensity forecast could not be effectively optimized using only the maximum tangential wind speed observations. In contrast, the joint parameter estimates are well constrained when the observations of the inner vortex core circulation are used. The results suggest that full kinematic field observations, such as Doppler winds measurements, are beneficial for optimizing the parameterizations with respect to the intensity prediction problem. It is also demonstrated that optimal estimation with observations would lead to mutually dependent estimates of the parameters. Such estimates would benefit the design of

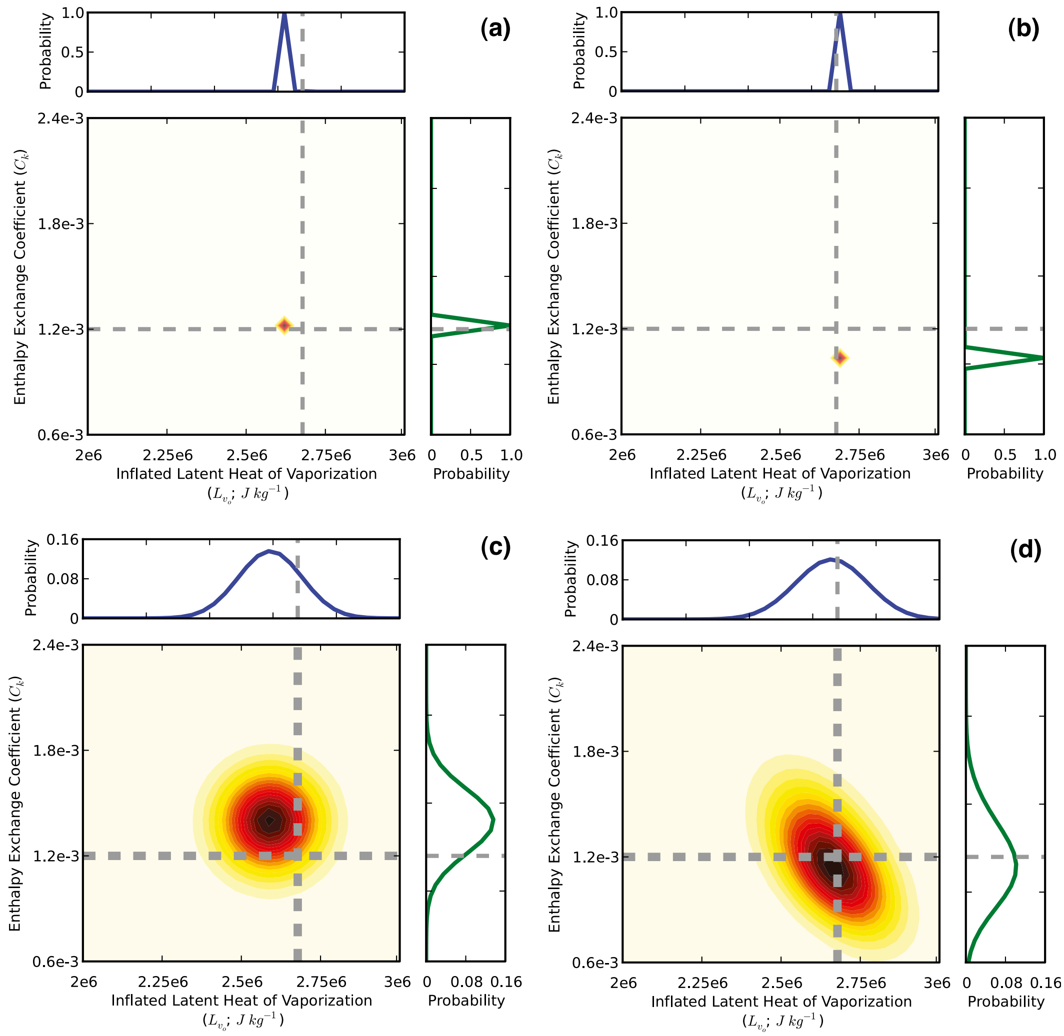

FIG. 4. As in Fig. 3, but using the kinematic field as the observable.

optimal parameter-based ensemble forecast perturbations. Although it would be difficult to compute a nonlinear inverse solution for full-physics, three-dimensional models because of the large dimension, more practical methods such as the ensemble Kalman filter data assimilation technique (e.g., Aksoy et al. 2006; Godinez et al. 2012; Yussouf and Stensrud 2012) could be applied with the full kinematic field observations. The efficacy of using such a method remains a question for future studies.

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