# REMOTE SENSING AND DATA ASSIMILATION FOR SURF ZONE BATHYMETRIC INVERSION

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We demonstrate the implementation and validation of a surf zone forecasting system, which uses remote sensing observations to control errors in surf zone bathymetry. This system uses ensemble-based sequential data assimilation techniques, which are adaptable to arbitrary geophysical observations, and/or arbitrary improvements to model physics. The system is validated using data from a 2010 field experiment at Duck, NC (U.S.A.), and is shown to produce accurate corrections to bathymetry, leading to improvements in prediction of currents.

Keywords: data assimilation; bathymetry; forecasting

# INTRODUCTION

The dynamic nature of nearshore bathymetry is an important factor for prediction in the surf zone. Bathymetry can change rapidly (even on time scales of less than one day, Lippmann and Holman (1990)), and has a strong influence on waves and currents. Morphological models exist which attempt to predict these changes, but at present the physics in these models are still being developed (e.g., Hoefel and Elgar (2003); Henderson et al. (2004)), and even the fundamental topic of predictability in these systems is a subject of ongoing research (Coco and Murray, 2007; Plant et al., 2006). As a result, bathymetry error can play a leading order role in the accuracy of predicted waves and currents. This was demonstrated well by Allard et al. (2008), who implemented and tested a sophisticated nearshore forecasting system, and identified bathymetric uncertainty (due to movement of sand bars) as a primary source of model error.

Based on this, it would seem that continual bathymetric monitoring would be necessary if one is attempting to predict surf zone waves and currents over time scales of more than a few weeks. However, direct observation of bathymetry is often prohibitively expensive or even impossible depending on the region being studied. For this and other reasons, innovative methods for estimating bathymetry have been developed by various authors. In particular, a number of bathymetry estimation methods have been proposed using measurements of surface wave celerity obtained from remote sensing. These methods rely on the relationship between wave celerity and depth in the form of a dispersion relation (e.g. Stockdon and Holman (2000)). Although error may occur if one is unable to account for finite-amplitude effects and/or the effect of unknown currents on waves (Holland, 2001; Catalán and Haller, 2007), these celerity-based methods can generally produce accurate and reliable results. Even better accuracy can be obtained if measurements are integrated sequentially over a long period of time, as in the beach profile estimator developed by VanDongeren et al. (2008) which is now being extended for fully-3D bathymetric estimates using full-field video imagery by Holman et al. (2012).

Meanwhile, advances in remote sensing techniques are beginning to produce new data products which have potential applications in the surf zone, such as techniques for estimating currents (Chickadel et al., 2003), and wave direction (Holman et al., 2012). These push the limits of the standard methodology above, which was developed mainly for observations of wave celerity. This provides motivation for pursuing more general methods of data assimilation. Such an approach was taken by Wilson et al. (2010), who demonstrated that surf zone bathymetry could be estimated from observations (in-situ) of wave height and alongshore current. The advantages of this approach are it allows for estimation is performed within the framework of a numerical forecasting system, which is an advantage if forecasting (not just bathymetric prediction) is the end goal of the analysis. The main disadvantage lies in the complexity and computational cost of such a system, which may be unreasonable depending on the needs of the user.

Our goal in the present work is to show how the methods used by Wilson et al. (2010) can be implemented as a forecasting system, using remote sensing data alone to control errors due to bathymetric uncertainty over time. This system is tested using remote sensing data from a 2010 field experiment at Duck, NC, U.S.A., and is shown to produce accurate corrections to bathymetry which lead to improved prediction of surf zone currents.

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Figure 1: Contour map of measured bathymetry in model domain during September 2010 Duck NC field experiment. Depths are shown in meters relative to the National Geodetic Vertical Datum. The location of the FRF pier is marked for reference by the thick black line.

## **OBSERVATIONS**

Herein, we will make use of three remote sensing data products: one which measures wave celerity, and two which measure alongshore currents. All three of these products will be assimilated by our system, and are provided on 1/2 hour collection cycles. The first product is optically-derived maps of wave celerity, estimated using the method described in Holman et al. (2012). The second is optically-derived estimates of alongshore current, estimated on five alongshore transects in the surf zone (25 m across-shore spacing, starting at x = 125 m), using the method of Chickadel et al. (2003). The third is Particle Image Velocimetry estimates of alongshore current, estimated from an infrared video system similar to the method of Chickadel et al. (2009).

These observations were collected as part of a September 2010 field experiment at the Field Research Facility (FRF) in Duck, NC, U.S.A. Figure 1 shows the measured bathymetry in our model domain, and defines our coordinate axes (standard for the FRF). The remote sensing measurements used here span a range of 550 < y < 900 m. The southward limit, y > 550 m, was chosen in order to neglect possible effects of the FRF pier, which is not accounted for by the model and/or the remote sensing data processing; the northward limit, y < 900 m, was chosen to exclude far-field remote sensing measurements (which may be inaccurate due to decreasing camera resolution), and to avoid areas close to the artificial model boundary.

#### **METHODOLOGY: MODELING SYSTEM**

The present method closely follows Wilson et al. (2010), and will not be described in detail here. To extend the method for application to time-varying sequential assimilation of data, we define the following update scheme which we apply each time observations arrive:

- 1. Apply the update step to each individual member of the N = 250 member ensemble, resulting in a posterior ensemble. Note we must add random perturbations to the observations in this type of update, see Houtekamer and Mitchell (1998).
- 2. Compute an Empirical Orthogonal Function (EOF) decomposition of the updated ensemble.
- 3. Extract the mean and standard deviation of the resulting N = 250 EOF scores.
- 4. Resample the EOF scores *N* times using a Gaussian random number generator, with the same mean as above, and an inflated standard deviation, 5% larger than above.
- 5. Reconstruct a new bathymetry ensemble from the N = 250 resampled EOF scores.

This updated bathymetric ensemble is then used as the prior for the next assimilation time window. Note the use of inflation accounts for unknown process error, similar to VanDongeren et al. (2008). Inflation is also necessary to mitigate the possibility of filter divergence, a well-known problem in the application of sub-optimal approximate filtering algorithms (Hamill et al., 2001).

The above scheme serves to update the bathymetry ensemble using observations, based on the dynamics described by our forward model, described next. The forward model used to predict wavenumber uses the

dispersion relationship proposed by Kirby and Dalrymple (1986), recommended by Catalán and Haller (2008) for use in depth inversion, and includes the effects of both finite wave amplitude and currents. The forward model used to predict waves and currents employs a combination of SWAN (Booij et al., 1999), and the Regional Ocean Modeling System (ROMS, Shchepetkin and McWilliams (2005)). SWAN is initialized at the offshore boundary by wave spectral measurements from the FRF 8m-array. Default values for physical parameterizations are used throughout in our SWAN model. ROMS is run in depth-uniform mode, and is forced by static radiation stress gradients from SWAN. Bottom stress is parameterized using the method of Svendsen and Putrevu (1990), with a drag coefficient  $f_w = 0.0053$  (chosen based on an analysis of field data on this beach by Feddersen and Guza (2003), for a similar (though not identical) bottom stress formulation). Surface stress is assumed to be due to wind only, and is modeled using the parameterization of Smith (1988), using wind measurements from the offshore end of the FRF pier (nominal values are assumed for air temperature,  $10^{\circ}$  C, and density,  $1.22 \text{ kg/m}^3$ ). Momentum mixing is modeled with an eddy viscosity, parameterized as in Haas et al. (2003). Tides are included as a static adjustment to the water level, as measured by a tide gage at the end of the FRF pier (note, this implies the sub-tidal depth is what is uncertain in our system, not the total water depth). The shoreline boundary condition is no-slip, applied at the 10 cm depth contour, and a radiation condition is applied at the offshore model boundary. The lateral boundary conditions are assumed periodic, and a 300 m wide buffer zone is used to enforce periodicity in model inputs.

Because the bathymetry is updated suddenly in our modeling system at the beginning of each observation cycle, the problem is most easily treated as quasi-steady. Hence, SWAN is run in stationary mode. Similarly, ROMS is initialized from rest, allowed to spin-up for 3 hours, and then model outputs are averaged over 30 minutes to simulate an observational data collection period. This process is repeated each time bathymetry is updated.

## RESULTS

To validate our modeling system, we now apply it using the remote sensing data described above, for a time period of 0800 EST to 1830 EST on September 13, 2010. Recalling that the observations are defined on a 1/2 hour basis, this involves a total of 22 assimilation cycles. The test covers nearly a full tidal cycle, and occurred during moderate wave conditions (significant wave heights 0.5–1 m, nominal surf zone currents of 0.5 m/s).

Figure 2 (middle panel) shows the final estimate of bathymetry at the end of the assimilation window. This is compared to the initial estimate for the beginning of the window (left panel), which was defined using a bathymetric survey conducted 47 days prior to the observation time. We also compare to a more recent survey, conducted only 7 days prior to the observation time. The estimate captures several important bathymetric features which had developed in the intervening days between the two surveys. For instance, the estimate captures a large shoal located at approximately y = 700 m; this shoal was responsible for significant alongshore-nonuniform flows observed in this time period, hence was a very important feature dynamically. Similarly, a channel-like feature at approximately y = 850 m was also partly captured. And finally, the offshore region x > 250 m was made shallower by the assimilation of data, in agreement with the measured changes. These corrections resulted in an increase in bathymetric accuracy due to assimilation of data: using the September 6 survey for verification, in the domain shown in Figure 2, the root-mean-square error was 30 cm, compared to 40 cm if no data were assimilated.

## DISCUSSION

The present work suggests remote sensing data alone is sufficient to provide useful information on surf zone bathymetry. This information can be used to control bathymetry error in a numerical model. This represents progress towards a surf zone forecasting system which can be driven by remote sensing data alone, without relying on continual bathymetric surveys. A remaining barrier to this application would be the specification of offshore boundary conditions, which in our case are still obtained by in-situ means. However, this would not be important for a forecasting model, which would naturally use boundary conditions from existing large-scale wave forecasting/hindcasting systems. Another necessary challenge for an operational forecasting system would be calibration of the inverse model. The state of the art in data assimilation, including the system used here, involves the use of Gaussian-based estimators, and approximate update steps (e.g. using ensemble estimates). As mentioned above, this necessitates the use of tricks



Figure 2: Results after assimilation of 22 observation cycles. Left panel: initial prior bathymetry, survey on July 28; middle panel, resulting estimated bathymetry for September 13, 1830 EST; right panel: vertication, measured bathymetry from September 6. Bathymetry is plotted in meters below National Geodetic Vertical Datum (colorbar in top right).

such as covariance localization and inflation to ensure the estimate remains stable and viable over time. These factors must be calibrated based on experience and cross-validation, which we have only begun to do here. Similarly, an operational system would require observational data to be carefully vetted for quality, and given appropriate error bars. Of particular concern for remote sensing data is the question of spatial covariance of observation errors. This is an important topic for future work.

The main advantage of the present ensemble-based method is it is easily adaptable to arbitrary geophysical observations and/or arbitrary updates to model physics; essentially, the numerical model and the extraction of observations from that model are treated as a "black box" from the standpoint of the inverse model. The main disadvantage of this method is ensemble computations are limited by computational resources, hence they can be expensive, and they are always approximate. One way to avoid this expense is to use smaller ensemble sizes, but this leads to increased reliance on ad-hoc methods for mitigating filter divergence, e.g. increased covariance localization and inflation (Hamill et al., 2001). Such approximations are not as important when using variational methods (Bennett, 2002), but the tradeoff is in terms of the adaptability mentioned previously. Finally, depending on the application methods such as VanDongeren et al. (2008) or Holman et al. (2012) may be very accurate and require much less computational expense; in that case, the tradeoff is a reliance on wave celerity-based estimators, which may not be useful in certain environments (e.g. when waves are not present, as in a river or inlet/estuary, Wilson and Özkan Haller (2012)).

#### CONCLUSIONS

We have presented an application of data assimilation for controlling bathymetric uncertainty in a surf zone model, using remote sensing observations alone. Our results show that remotely sensed observations of wave-averaged currents and wave celerity can both provide meaningful information about surf zone bathymetry. In turn, this information can be extracted by statistical means (data assimilation) to predict or control bathymetry.

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