This project presents the successful integration of a data assimilation framework and a nonhydrostatic coastal ocean model for the study of sub-mesoscale processes and state variables. When provided with the proper data, mesoscale phenomena have been modeled with a certain level of accuracy; however, many sub-mesoscale features are still poorly modeled, causing them to remain largely unpredictable from deterministic event and statistical property standpoints. 3D nonhydrostatic models are required to accurately capture these key dynamics. Although this implementation is essential for the successful development of physical ocean models, a major challenge posed by this approach is the high computational cost incurred by high-resolution numerical models with three-dimensional data assimilation schemes within complicated, stratified systems. However, by interfacing our General Curvilinear Coastal Ocean Model (GCCOM) (model developed at the San Diego State University (SDSU) Computational Science Research Center (CSRC) with NCAR’s Data Assimilation Research Testbed (DART), we were able to integrate very high-resolution observations into the system. Our research included observation system simulation experiments (OSSEs) for test cases using very steep seamounts. Our results demonstrated that the DART-GCCOM model can successfully assimilate high-resolution observations (to tens of meters) using as few as 30 ensemble members.

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Fig 1. Example of a 3D visualization of GCCOM model output at time-slice of 6 hours.

Fig 2. The variable of interest (in this case the U component) was assimilated every 10 minutes over 6 hours of simulation time. The mesh was approximately 3.5 km (longitude) x 2.5 km (latitude) x 1 km (depth) of 97x32x32 grid points, respectively.

Fig 3. Last 3 hours of forecast rank histogram. 30 ensemble members at depth -498 m localization of 2000 m. Rank histogram with the correct spread observation error variance 1.0, 0.9, 0.8 (top). Rank histogram indicating insufficient spread; observation error variance 0.5 and 0.1 (bottom).

Fig 4a-4b: Spread evolution plot at depth 897.9028 m (left) and time-space average of the spread (right) for a variable U component after spin-up time, for observation error variance 1.0, 0.9 and 0.8.

Fig 5a and 5b. Vertical cross-section for U component at two different assimilation steps. Top: True State; Middle: Prior; Bottom: Distance (True-Prior). As assimilation evolves the distance between true and forecast decreases.

Fig 6. Time evolution absolute error (or distance) [True-Prior] for a vertical profile of the U Component for an observation error variance of 1.0, 0.9, 0.8 and 0.5 (from top-to-bottom) with a localization of 2000 m.