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Verification and training of real-time forecasting of multi-scale ocean dynamics for maritime rapid environmental assessment

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Abstract

The Harvard Ocean Prediction System (HOPS) provides real-time and hindcast, multi-scale oceanic field estimates for Maritime Rapid Environmental Assessment (MREA). Results of aspects of the validation, calibration and verification of HOPS for MREA03 and MREA04 are presented, with implications for future MREA exercises. A new method of model training, via bias correction through the use of limited data, was applied to MREA03 and shown to produce significant forecast improvement while reducing computational requirements. Advances in, and the demand for, adaptive modeling, require that aspects of validation, calibration and verification be carried out in real-time in order to expand the usage and relevance of dynamical forecast-based MREA tactical decision aids.

Keywords: Prediction; Models; Operational oceanography; Multi-scale analysis; Bias correction; Mediterranean Sea; Elba; Portugal

1. Introduction

The ability to forecast multi-scale ocean dynamics is a critical component of Maritime Rapid Environmental Assessment (MREA), the timely acquisition and analysis of tactically relevant environmental information (Pouliquen et al., 1997; Kirwan and Robinson, 1997), and is now a critical component of the NATO Tactical Ocean Modeling System (NTOMS; (Coelho and Robinson, 2003; Coelho et al., 2004; Rixen and Ferreira-Coelho, 2006, 2007; Rixen et al., 2007). Analysis of detailed environmental information provides a static view of conditions, but dynamical forecasting provides the picture of evolving fields for tactical decision making. Ocean forecast systems have been developed to provide nowcasts and forecasts of ocean circulation from global and basin scales to the mesoscale and sub-mesoscale. The Harvard Ocean Prediction System (HOPS) is such a forecasting system and the utilization of HOPS in MREA03 and MREA04, both in support of specific objectives of the exercises and for general development of the HOPS system, is the purpose of this paper.

HOPS is an integrated system of data analysis and data assimilation schemes and tools, and a suite of coupled interdisciplinary (physical, acoustical, optical,

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biogeochemical–ecosystem) dynamical models (Robinson et al., 1998; Robinson, 1999; Robinson and Lermusiaux, 2002, 2004). HOPS was developed to produce real-time and hindcast, interdisciplinary, multi-scale oceanic field estimates that include effective and efficient data assimilation, dynamically consistent model initialization, multi-scale nesting, and model-driven adaptive sampling with feedbacks. Since the early 1980s HOPS has evolved and progressed while providing usefully accurate estimates of ocean fields in a timely and reliable manner for real-time exercises throughout the world's oceans, including several recent MREA exercises. These MREA exercises have provided valuable venues for the development, testing, and implementation of the HOPS system concept and software as well as the development of NTOMS, which includes HOPS among its ensemble of ocean modeling systems.

HOPS has generally used a regional strategy to forecasting, employing relocatable nested model domains of increasing resolution. The domains of operational interest are the most highly resolved and a significant effort is made to initialize them realistically. This can be done by: i) dedicated initialization surveys or, ii) with a combination of historical synoptic data and satellite remotely sensed data, together with feature models (Gangopadhyay and Robinson, 2002). In the latter case, data assimilated during the exercise is expected to improve the forecasts. In any case, in evaluating the forecast system's skill, including the dynamical model skill, the quality and quantity of data must be considered.

A Mini-HOPS sub-regional strategy, which utilizes small, high-resolution, low computational requirement model domains, has been developed to provide more rapid data assimilation focused on areas of observations, regions of high forecast uncertainty and/or sites of tactical interest. The Mini-HOPS concept is designed to locally solve the problem of accurate synoptic representation of sub-mesoscale (e.g. high frequency, inertial or near-inertial motion) processes. This concept involves real-time assimilation of high-resolution data into the Mini-HOPS domains.

An important aspect of the development and evolution of HOPS has been the validation, calibration and verification of the system for each of the various exercises for which it has been utilized. These concepts were first introduced in Robinson et al. (1996) and their further developments and utilization are overviewed in Robinson and Sellschopp (2002). *Validation* (general applicability to local dynamics and structures) and *calibration* (physical, domain and computational parameters tuned to the region and specifics of phenomena during the exercise) are carried out *a priori* whenever possible via the use of historical synoptic or climatological data. *Verification* (quantitative determination of the accuracy of model prediction) is generally carried out *a posteriori*. Advances in adaptive modeling, the evolution of forecast systems in response to modeled or observed processes, require that aspects of validation, calibration and verification now be carried out in real-time. A scheme for model training based on limited observations has been developed that helps to provide that ability. Model training refers, in general, to the two-fold problem of error parameter and model parameter estimation based on observational data (Logutov and Robinson, 2006). Model–data misfits and model–model differences within a multi-model system provide a source of information for determining systematic and random errors in forecasts and for tuning model parameters. For MREA03 a form of model training was employed; empirical calibration based on prior model misfits**.** This paper focuses on interesting advances in calibration and verification in the MREA03 and MREA04 exercises, including calibration in real-time.

2. Model description

Detailed descriptions of HOPS can be found in Robinson (1996, 1999), Robinson et al. (1996) and Lozano et al. (1996). The heart of HOPS is a rigid-lid primitive equation physical dynamical circulation model (a free surface version of the dynamical model has been implemented since the MREA exercises). The prognostic variables are arranged on an Arakawa B grid, and a double-sigma vertical coordinate system is calibrated for accurate modeling of steep topography. Horizontal sub-grid scale processes are parameterized by a Shapiro filter (Shapiro, 1970; Robinson and Walstad, 1987), vertical diffusion is formulated as a second order diffusion term in a Richardson number dependent scheme similar to that of Pacanowski and Philander (1981). Near horizontal and vertical rigid boundaries, Rayleigh friction is applied using a Gaussian weighting of distance from the bottom or the coast, respectively (Lermusiaux, 1997). The mixed layer physics is formulated according to Niiler and Kraus (1977). Implicit Orlanski (1976) radiation conditions are applied to the lateral open boundaries for tracers, velocity and streamfunction. For the rate of change of barotropic vorticity, the boundary condition used was a Charney–Fjortoft–von Neumann radiation condition as derived by Spall and Robinson (1989). Optimal Interpolation (Carter and Robinson, 1987; Robinson et al., 1998) is used to generate assimilation fields of temperature and salinity from the initialization and update surveys. These fields are assimilated with linearly increasing assimilation weight towards their nominal time ("ramping"). The bathymetry is primarily from DBDB-V (NAVOCEANO), with higher resolution bathymetry merged in where available.

Atmospheric forcing fields required by HOPS for MREA03 and MREA04 were acquired from the US Navy Fleet Numerical Meteorology and Oceanography Center (FNMOC). The FNMOC fields include surface pressure, air temperature, 12-hour forecast precipitation, surface winds, relative humidity, cloud cover, sea surface temperature and mixed layer depth. The model and analysis fields, including 00Z and 12Z nowcasts and forecasts for up to 144 h on a 1-degree or 2-degree resolution grid, were downloaded via the Internet. These gridded fields were interpolated in space and time onto the HOPS model grids and used to compute fluxes that drove the HOPS models at the surface. Flux analyses were used whenever possible and forecast fluxes were replaced by the analyses as those analyses became available. For MREA03, higher resolution wind fields (0.1°) were provided by the ARPEGE–ALADIN model.

3. Maritime rapid environmental assessment 2003 (MREA03)

MREA03 took place in May/June 2003 in the Corsican Channel near the island of Elba in the Mediterranean Sea. The overall MREA03 objectives were: 1) operational modeling statistical analysis; 2) covert beach access environmental reconnaissance; 3) real-time beach experiment; 4) sub-mesoscale real-time modeling; 5) high-frequency acoustic variability; and, 6) real-time data fusion and display. The HOPS MREA03 scientific objectives were to: 1) carry out and quantitatively evaluate a multi-scale real-time forecast experiment; and, 2) carry out a sub-mesoscale experiment to characterize sub-mesoscale/inertial dynamics in an area of the channel north of Elba (MREA03 objective 4). The second objective arose from the development of the concept of Mini-HOPS. Mini-HOPS initializes, forecasts and updates small, high-resolution (sub-mesoscale) domains focusing on areas of observations and/or tactical interest. Mini-HOPS domains have reduced computational needs, allowing forecasts in these domains to be run more rapidly. This rapid forecast capability leads to the potential for real-time adaptive modeling, reducing local uncertainty and improving tactical forecasting. Insight gained from the Mini-HOPS forecasting can be combined with the data collected today and used in the forecast for tomorrow.

The hydrographic data for MREA03 was collected by the NATO Research Vessel (NRV) Alliance. A total of 462 CTD casts are available over the time period 28 May–25 June 2003. The station positions for all surveys are shown in Fig. 1. An initialization survey from 28–31 May covered the complete sampling area. Adaptively sampled updating data was gathered from 3–9 June. An initialization survey for the Mini-HOPS domains took place on 12–13 June. Dedicated Mini-HOPS surveys were carried out from 13–17 June. Verification data was

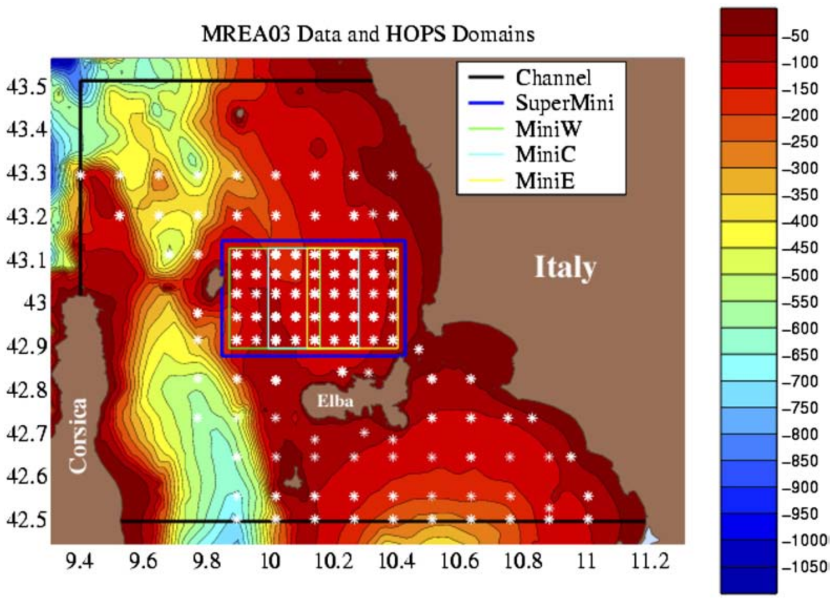

Fig. 1. Positions of MREA03 observations and HOPS nested modeling domains superimposed over bottom topography.

collected in the Mini-HOPS domains from 19–22 June and in the larger area of interest from 23–25 June. The high-resolution sampling in the Mini-HOPS domains was carried out in order to evaluate the accuracy and persistency of the sub-mesoscale, short-term forecasts and observed features. Limited remotely sensed data (SST) was not assimilated but was used for qualitative comparison with model results.

The MREA03 HOPS system consisted of a set of two-way nested domains (Fig. 1). The Channel domain encompassed the initialization survey with a 1 km horizontal resolution. The SuperMini domain and Mini-HOPS domains (MiniW, MiniC, and MiniE) each have a 1/3 km horizontal resolution. The SuperMini domain was initialized from and two-way nested with the regional (Channel domain) HOPS run. The SuperMini domain provides a buffer region between the Channel domain and the Mini-HOPS domains in which the dynamics is influenced by both the coarse and fine resolution dynamics. In particular the SuperMini domain gives: i) boundary conditions for the mini domains that are dynamically adjusted to the finer resolution; ii) feed-back from the fine resolution physics to the coarser grid; and, iii) the fine resolution dynamics of the entire Mini-HOPS survey region.

Real-time analyses and forecasts were issued via the web for the period 11–17 June 2003. These were available to those aboard the NRV Alliance for adaptive sampling and identification of circulation features. Each real-time product page contained a description of the data being utilized in initialization and assimilation, and a discussion of recent atmospheric forcing and its effects. Nowcasts, one-day and two-day forecasts of temperature and salinity were issued for four depth levels (5, 25, 50 and 100 m). Web products were issued only for the HOPS Channel domain. In addition to nowcast and forecast maps, initial and boundary condition data files were provided via the web to researchers aboard the NRV Alliance for at-sea Mini-HOPS modeling efforts. This at-sea modeling provides the ability for those at sea to rapidly respond to forecast conditions and, thereby, adaptively sample of areas of dynamical, logistical or tactical interest. The decision as to where to go today and tomorrow can be based on a forecast made today.

The *verification* of MREA03 forecasts was carried out both in real-time and *a posteriori*. HOPS forecast fields were in generally good agreement with observations throughout the exercise. A qualitative comparison of model results with SST is shown in Fig. 2. This figure compares remotely sensed observations with surface (5 m) temperatures on June 14, 2003 from a real-time HOPS forecast. While SST from satellite measures only skin temperatures, and contains effects not included in the dynamical model, it can provide an otherwise unavailable large-scale view of the structures in a region. Upwelling areas, fronts and jets are generally located in the model forecast where they are observed in the AVHRR image with appropriate shape, orientation and size. For example, upwelling cold waters are in evidence along the Italian coast, as well as a cool pool to the southwest of the island of Elba. However, overall the real-time HOPS is approximately 1 °C too cold, and the area south of Elba is several degrees colder in HOPS than observed. We attribute this, in part, to the fact that this area has not been sampled *in situ* for a week prior to the AVHRR image.

A quantitative comparison of observed profiles of temperature with those from real-time model results for June 15 (Fig. 3a) indicated that below 35 m the difference between modeled and measured temperature is essentially negligible. However, in the depth range of 5–35 m (the main thermocline) the real-time model set-up did not well represent the ocean's vertical structure. To determine the causes of this mismatch and to improve the ability of HOPS to more accurately represent the ocean, a post-experiment re-analysis of modeling procedures was conducted (re-*calibration*). The re-analysis process included: tuning model parameters for stability and agreement with profiles, improving vertical grid resolution near the surface and in the thermocline, correcting input net heat flux, and starting the simulation at the actual sampling time. The post re-calibration comparison (Fig. 3b) demonstrates the improved forecast capability and that HOPS has been brought into agreement with the data.

As a measure of model skill, model temperatures from the initial conditions (persistence) are also compared to both the observed temperatures (Fig. 3a). The persistence data is from May 29 while the observed and forecast data is from June 15. The insets of Fig. 3a and b indicate the bias and RMS difference between the forecast temperatures and observed data and the bias and RMS difference between persistence and the observed data. It is clear from Fig. 3a that the real-time temperature forecast profiles are closer to the observed temperature profiles in both bias and RMS from the surface to 10 m. From 10 m to 35 m persistence is more accurate. Below 35 m forecast temperatures and persistence are essentially equally accurate. Once the re-*calibration* procedure has been performed (Fig. 3b), the comparison indicates that the forecast is better than persistence at all depths. Water-column average values for these comparisons are presented in Table 1. The bias

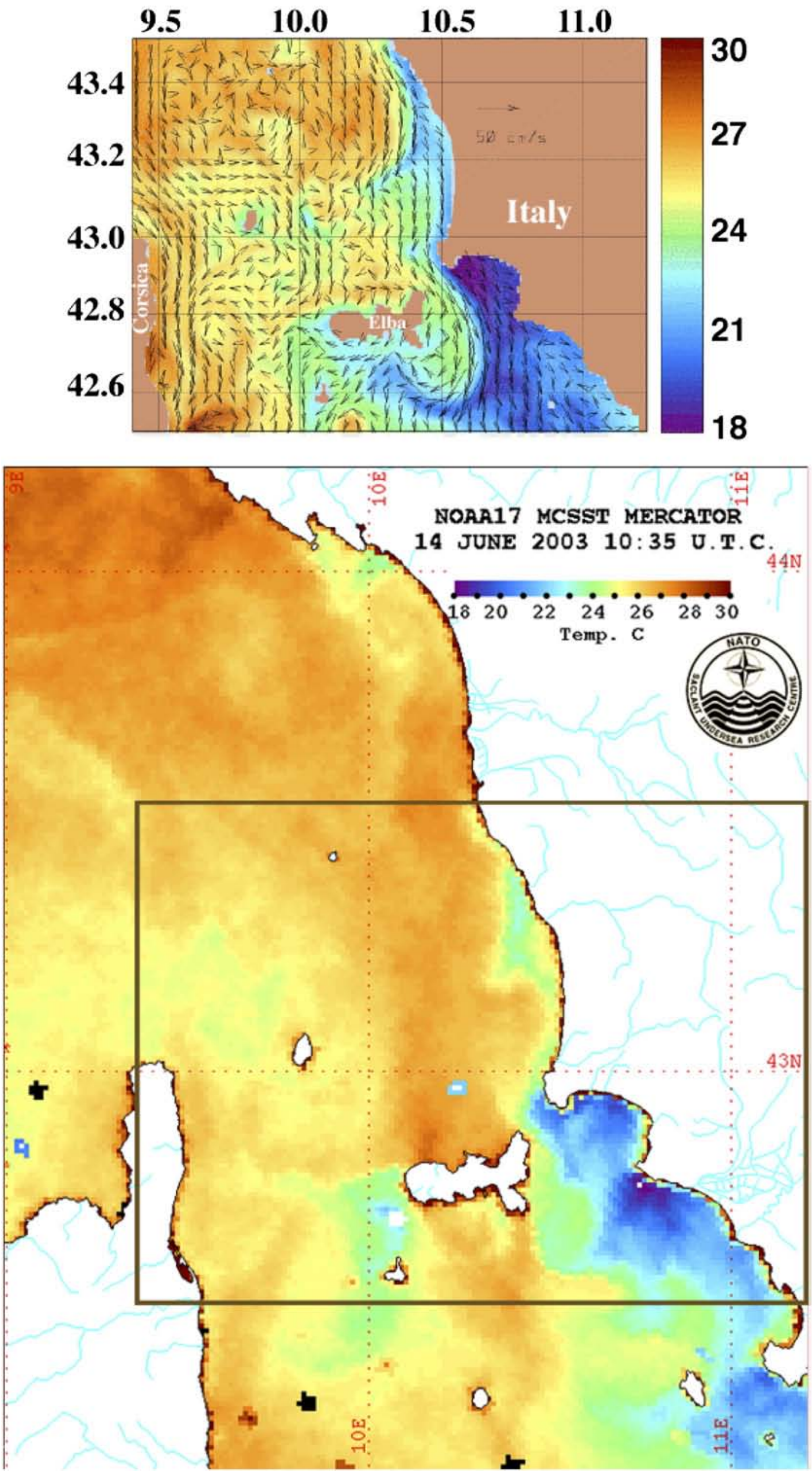

Fig. 2. Temperature on 14 June 2003; top) real-time HOPS 5 m forecast; bottom) remotely sensed sea surface temperature — the black outline approximates the HOPS model domain.

and RMS quantities were calculated at 10 m depth intervals and then averaged over the 10–140 m depth range. For temperature, during the real-time experiment, persistence was a slightly better representation of the observed profiles than were the forecast profiles. After the re-analysis, profiles from the HOPS model are

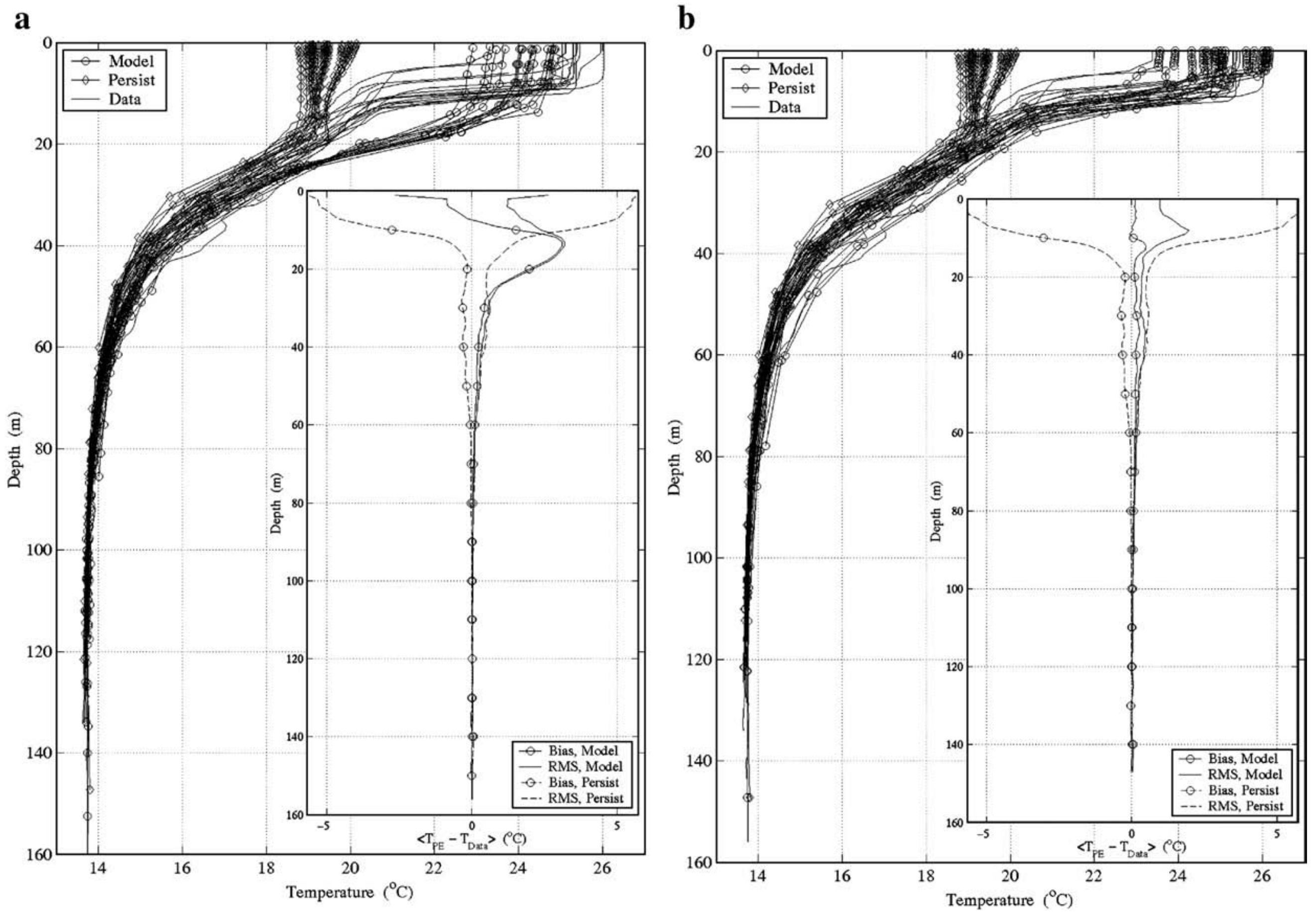

Fig. 3. Comparison of observed temperature profiles with profiles forecast by the HOPS model and persistence; a) real-time comparison; b) after re-analysis.

significantly better than persistence. For salinity, both the real-time forecast and the re-analysis profiles have better skill than does persistence.

Model initialization fields were created from a survey on May 28–31, 2003. Only limited data was gathered during the subsequent week. In real-time, due to this lack of data for assimilation and to computational instabilities (e.g. uncontrolled external velocity growth near islands) in model runs which resulted from inadequately tuned parameters, the forecasts which used these May 28–31 initialization fields were reset in time to appear as if they were from June 7. After the real-time experiment, parameters were tuned to improve the stability of the simulations. It was then possible to start model runs from May 28. Changes implemented in the units of forcing data received from FNMOC were also corrected *a posteriori*. Once the net heat flux was corrected, and, therefore, the atmospheric forcing was generating appropriate dynamical effects, the circulation evolved properly.

The largest effect on re-analysis results was obtained by refining the model vertical grid to be able to more accurately represent the vertical structure of the observed ocean. The original vertical grid was determined by an examination of the vertical structure of historical and climatological observations for this region and season and had been used in a previous (May 2002) forecast experiment in the same location. This vertical grid turned out to be inappropriate as the real-time observations had a vertical structure significantly different from the previous real-time experiment, as well as

Table 1
Mean Bias and RMS difference in temperature and salinity for MREA03 (10–140 m)

	T-forecast	T-persistence	S-forecast	S-persistence
Bias				
Real-time	0.3341	0.2772	0.0098	0.0199
Re-analysis	0.0810	0.3121	0.0063	0.0227
RMS				
Real-time	0.4412	0.4048	0.0205	0.0305
Re-analysis	0.2493	0.4107	0.0174	0.0311

from the historical and climatological data. Initial comparison of the real-time initialization survey profiles with those from the previous forecast experiment indicated some differences in the structure of water column. However, logistical constraints and needs of the real-time exercise prevented extensive modification and testing of the vertical grid. The evolution of the water column structure (significant warming and deepening of the mixed layer, i.e. development of the seasonal thermocline) during the exercise greatly increased the effect of the inappropriate vertical grid.

The original vertical grid included 20 vertical levels with relatively uniform structure throughout the water column, and slightly higher resolution at the top of the lower set of sigma levels. The re-analysis grid also contained 20 vertical levels but with much higher resolution within the top 40 m of the water column and significantly lower resolution at depth, where it is unnecessary. It is possible to determine the ability of the vertical grid to reproduce observed temperature profiles without dynamics by mapping the data to model vertical grid points and then linearly interpolating between those grid points. The difference between the observed temperature and the model representation is then calculated at the observation depths. The observed profiles and their representation on the model vertical grid are shown in Fig. 4. The RMS difference and bias are presented in the insets. The bias and RMS difference are both seen to be significantly reduced in the 5–15 m depth range with the implementation of the revised vertical grid.

The *verification* of MREA03 HOPS real-time results showed that the grid and physical parameters of the HOPS set-up needed to be modified. *Calibration* of HOPS procedures dramatically improved the characterization of the environment by HOPS, reduced forecast uncertainty, and enabled HOPS to better identify, define and characterize local dynamics.

4. Maritime rapid environmental assessment 2004 (MREA04)

MREA04 took place in March/April 2004 off the coast of Portugal. The overall MREA04 objectives were: 1) operational surface drift estimation from ocean, wave and meteorological modeling statistical ensembles;

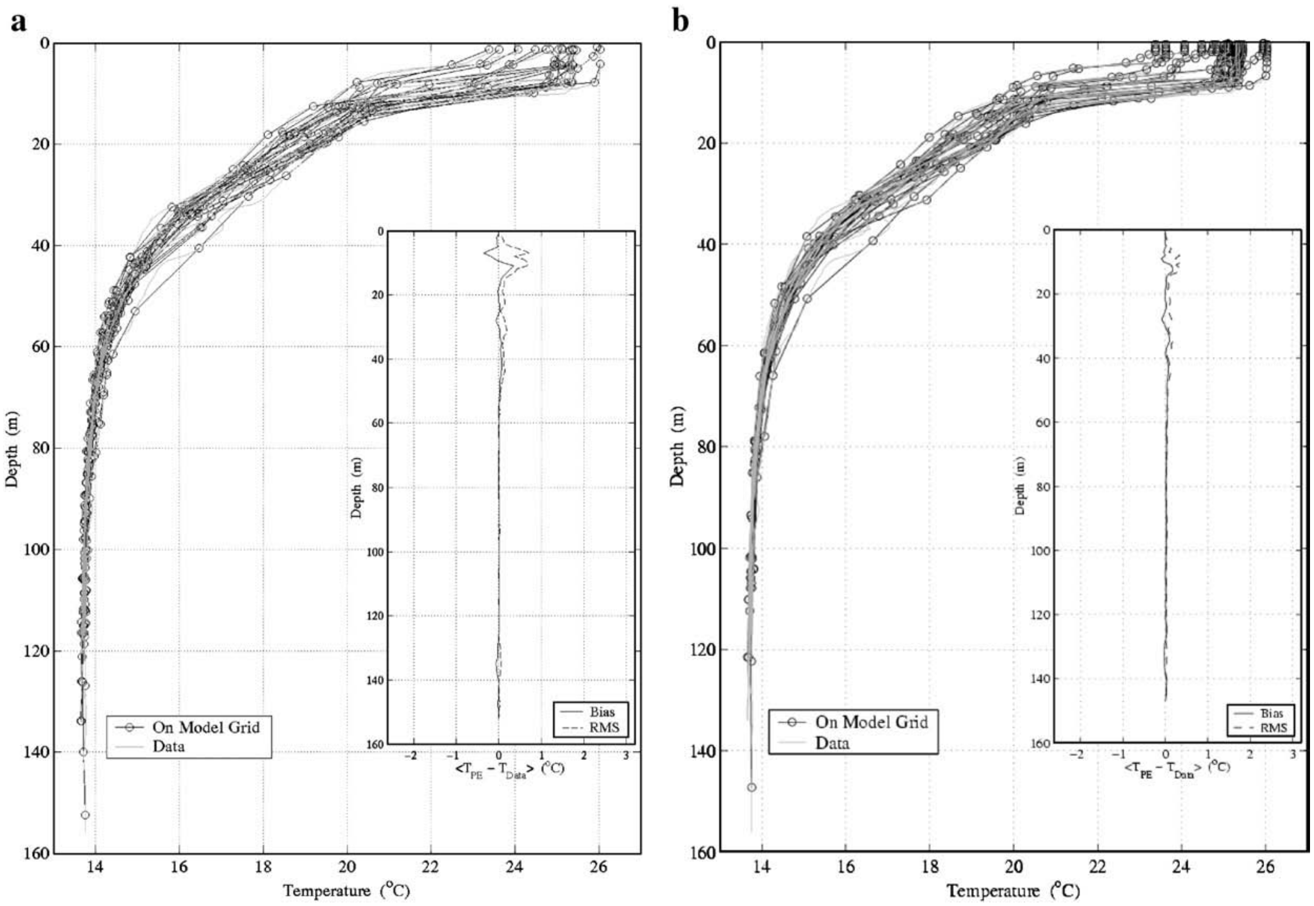

Fig. 4. Comparison of observed temperature profiles with profiles reconstructed on the model grid; a) real-time grid; b) after re-analysis.

2) beach environmental reconnaissance and monitoring for amphibious warfare support; 3) operational estimation of sub-mesoscale to small-scale sound speed structures in a coastal sea; and, 4) high-frequency acoustic tomography using drifting arrays and buoys. The HOPS scientific objective was to carry out a multi-scale (mesoscale and sub-mesoscale) real-time forecast experiment. The HOPS scientific goal was to support MREA04 overall objectives 1) and 3) by providing real-time estimates of temperature, salinity, currents and sound speed fields.

195 CTD casts were collected by the NRV Alliance over the period 31 March–16 April (Fig. 5). The time and space coverage of the profiles differ from the original plan. Weather conditions and other problems (e.g. transportation of a sick crewman) prevented the completion of all planned stations, leading to a notable lack of data along the northern and western boundaries of the Regional domain and the southern boundary of the SuperMini HOPS domain. The data was processed on a daily basis (as possible) and made immediately available for modeling.

The MREA04 HOPS set of two-way nested domains is shown in Fig. 5. The Regional domain spanned the initialization survey with a 1 km horizontal resolution. The SuperMini domain and Mini-HOPS domains (Mini X-North and Mini X-South) again all have a 1/3 km horizontal resolution. The Northern and Southern Mini domains encompass the planned mini-HOPS surveys

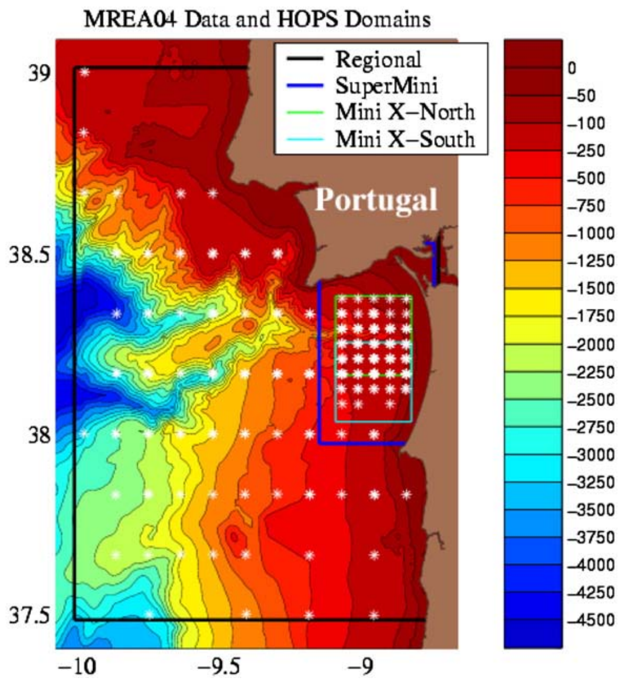

Fig. 5. Positions of MREA04 observations and HOPS nested modeling domains superimposed over bottom topography.

while avoiding placing a submarine canyon at a domain boundary. The SuperMini domain extends inward to the coast (resolving any coastal currents) and outward approximately 5 km beyond the minis (creating a buffer zone in which to adjust the coarser Regional domain physics). The Regional and SuperMini domain were run at Harvard in a 2-way nested configuration. Initial and boundary conditions for the Northern and Southern Mini domains were extracted (1-way nesting) from the SuperMini forecast. As the Northern and Southern Mini domains were collocated with the SuperMini and possessed the same resolution, this methodology avoided spatial interpolation issues while providing initial and boundary conditions adjusted to the fine grid resolution.

Real-time forecasts were released daily via the web for the period 6–10 April, 2004. This time period covers the Mini-HOPS dedicated sampling period. Data for the forecast initialization field is from 31 March–6 April. Each product release included maps and vertical sections in the Regional domain and the SuperMini HOPS domain of temperature, salinity and velocity. The maps are at four levels in the Regional domain (0, 10, 50 and 450 m) and the SuperMini HOPS domain (0, 10, 50 and 250 m). In the regional domain there are three sets of vertical sections — offshore-looking along 8.98°W and 9.7°W and northward-looking along 38.21°N. In the SuperMini HOPS domain there are two sets of vertical sections — offshore-looking along 8.98°W and northward-looking along 38.21°N. As in MREA03, in addition to the graphical products, data files were made available in real-time via the web to interested parties for forecast reproduction and investigation. At-sea Mini-HOPS efforts were planned for MREA04 but were unable to be completed due to logistical problems.

As post-experiment model *verification*, comparisons were made between *in situ* temperature and salinity profiles and profiles extracted from model forecasts at the location in space and time closest to that of the observation prior to that data being used for assimilation, providing RMS and Bias statistics of forecast quality. Comparisons with persistence (the model initial conditions) have been made as well. Included here are two examples of these results, using the data from 7 April and 8 April.

Fig. 6 identifies the positions of the observations utilized in the data/model comparison for 7 April. The time interval between the last profile collected during the initialization survey and the first profile collected on 7 April is approximately 41 h. The data is sampled within the Mini-HOPS domains but are being compared

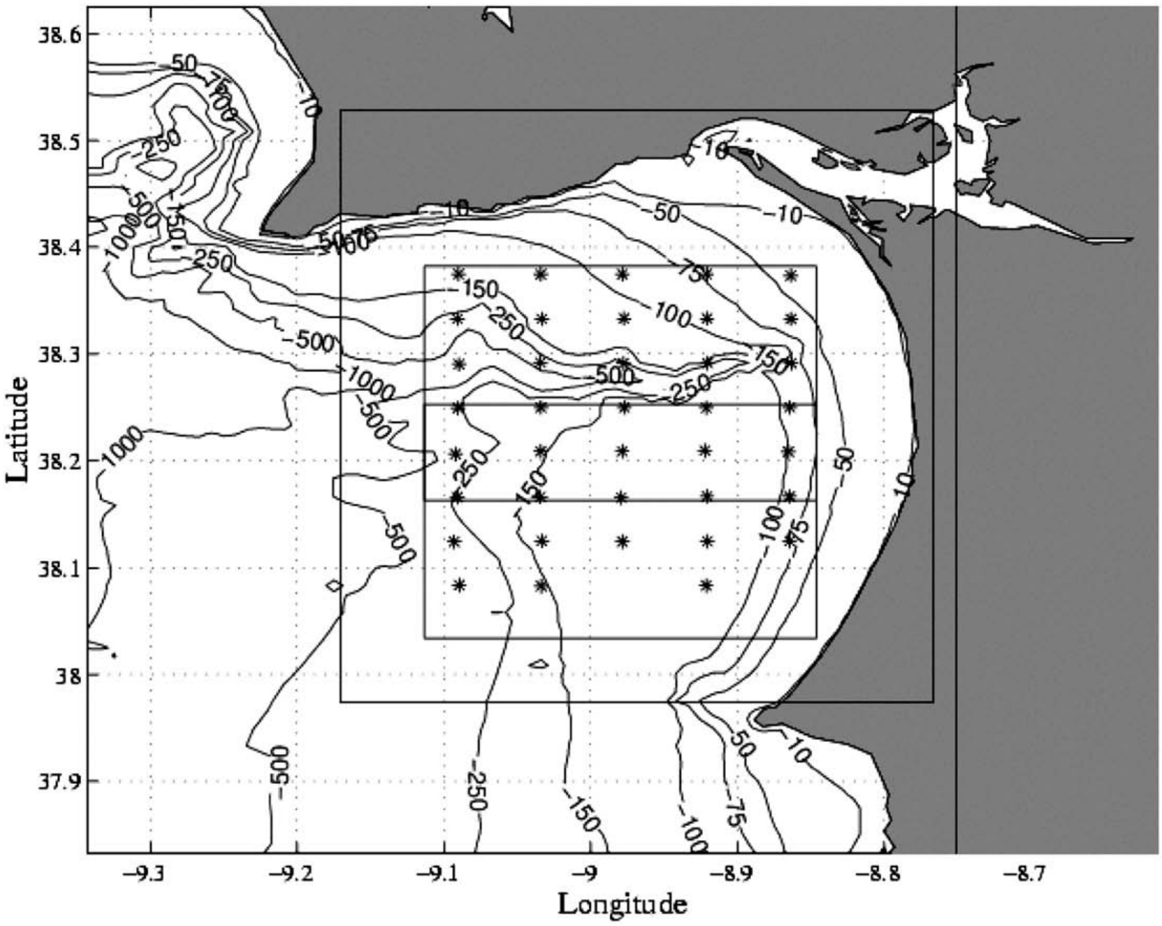

Fig. 6. Positions of CTD stations (asterisks) used in the data/model comparison for 7 April. Modeling domains are outlined.

with profiles sampled from the regional forecast. Fig. 7 shows the bias and RMS in the difference between temperature (Fig. 7a) and salinity (Fig. 7b) derived from model forecasts, persistence and *in situ* temperature and salinity. The temperature and salinity results are consistent. In the upper 15 m forecast profiles more accurately reflect the observations than do persistence. The model is capturing the dynamics of the upper mixed

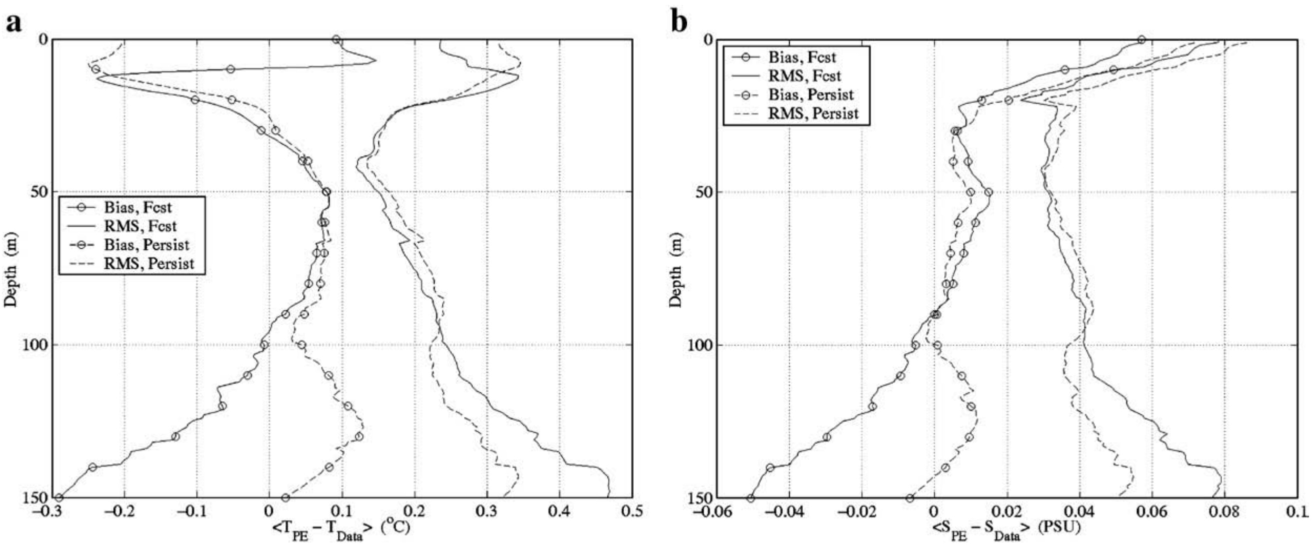

Fig. 7. Comparison of *in situ* observations on 7 April with HOPS model forecast profiles and persistence. a) 0–150 m temperature; b) 0–150 m salinity. In the figure legend, "Fcst" indicates forecast (solid lines), while "Persist" refers to persistence (dashed lines). Circles indicate bias.

layer. Between 15 m and 100 m forecasts and persistence are essentially equivalent. In this short forecast period little had happened dynamically in this depth range and persistence is a good estimate of the conditions. The dynamical model maintains these conditions as well. In the 100–150 m depth range persistence is better than the model forecast. It appears that dynamical adjustment processes in the model are happening too quickly at these depths for this time period. Below 150 m, comparisons are not statistically significant due to the limited number of observations.

Fig. 8 plots the positions of the observations utilized in the data/model comparison for 8 April. Fig. 9 shows the bias and RMS in the difference between temperature (Fig. 9a) and salinity (Fig. 9b) derived from model forecasts, persistence and *in situ* temperature and salinity. Once again the temperature and salinity results are consistent. Examining the RMS difference we see that forecast temperature and salinity profiles more accurately reflect observed conditions than persistence. Temperature difference bias presents a more complicated picture. In the 0–25 m range, forecasts are less biased than persistence. In the 25–50 m depth range the comparison is essentially equal. Below 50 m the difference in bias between forecasts and persistence remains roughly the same, but from 50 m to 90 m persistence bias (nearly zero) is smaller than forecast bias, while from 90 m to 150 m forecast bias is closer to zero than persistence bias. Over the entire depth range, salinity forecast bias is less than or equivalent to persistence bias. For this apparently more dynamically active day the model "beats" persistence. Water-column average values for these comparisons are presented in Table 2. The bias and RMS quantities were calculated at 10 m depth intervals and then averaged over the 10–150 m depth range. For both temperature and salinity, it can be seen that for April 7, persistence is slightly better than the model, but for April 8, the roles are reversed, with the model being more accurate than persistence.

HOPS real-time forecasts for MREA04 are more accurate than those for MREA03. Potential HOPS set-up problem areas had been identified via the *verification* and *calibration* re-analysis process of MREA03.

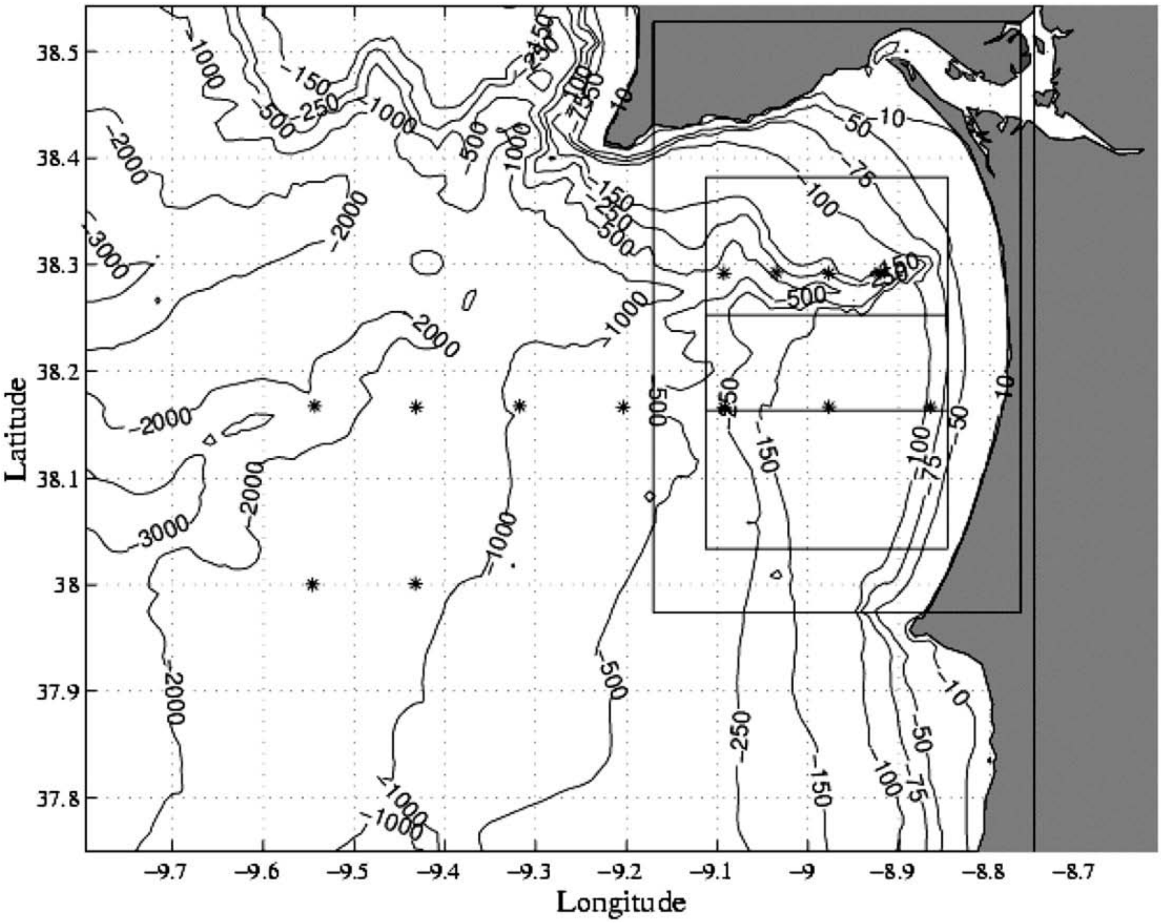

Fig. 8. Positions of CTD stations (asterisks) used in the data/model comparison for 8 April. Modeling domains are outlined.

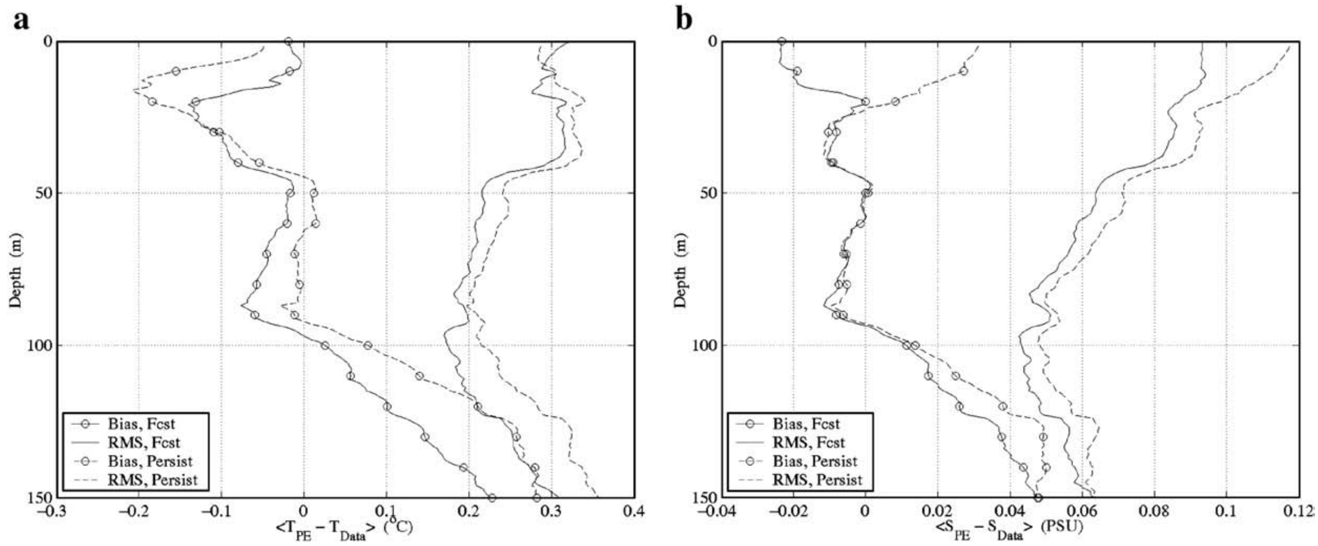

Fig. 9. Comparison of *in situ* observations on 8 April with HOPS model forecast profiles and persistence. a) 0–150 m temperature; b) 0–150 m salinity. In the figure legend, "Fcst" indicates forecast (solid lines), while "Persist" refers to persistence (dashed lines). Circles indicate bias.

Therefore they were avoided in real-time during MREA04.

5. Model training

Model training, for MREA03, refers to model error parameter estimation and systematic error correction based on observational data. Model-data misfits provide an important source of information that can be utilized in an on-line fashion, as new validation data become available, to learn error parameters. Modern regional ocean prediction systems can rely on methodologies for *adaptive* error parameter learning. Since regional applications error patterns often vary significantly across forecasting events in response to changing dominant ocean processes and conditions, we found that adaptivity is a key in determining a successful bias correction methodology. We find that a Bayesian approach which provides a utility for combining the prior information about error parameter values with the new information collected during the current forecasting event is well-suited for adaptive bias learning in regional ocean applications. Logutov and Robinson (2006) discuss the random error adaptive learning using a Bayesian principle. Within this approach, only a few most current batches of validation data (possibly just one batch) are used to infer error parameters by maximizing the likelihood expression for the parameters. The prior information about error parameters (if available) is also kept in the likelihood expression, with its assigned uncertainty, by using the Bayes theorem.

Following Dee and da Silva (1998) and Dee (2005), we parameterize the systematic error covariance in terms of the forecast error covariance, with a tunable coefficient of proportionality. The forecast error covariance parameters include error variance and length scale at an individual model level, the vertical correlation between errors at various levels, and the spatial correlation function. The tunable parameters are found from model–data misfits within a selected time window using the Maximum–Likelihood principle. Given a batch of model–data misfits, the bias update rule corrects the prior estimate of a bias (if any) using the systematic error covariance matrix as described in Dee and da Silva (1998). The systematic error covariance and the forecast error covariance are then updated using the Bayesian principle to include the most recent batch of model–data misfits (Logutov and Robinson, 2006). Robust regularization procedures are utilized to ensure that parameter estimation leads to a consistent solution.

Although HOPS MREA03 forecasts were largely calibrated and verified *a posteriori*, we have carried out the experiments in which only limited data were used for training in order to explore the benefits of the

Table 2
Mean bias and RMS difference in temperature and salinity for MREA04 (10–150 m)

	T-forecast	T-persistence	S-forecast	S-persistence
Bias				
April 7	0.0814	0.0775	0.0174	0.0095
April 8	0.0858	0.1198	0.0161	0.0199
RMS				
April 7	0.2570	0.2351	0.0446	0.0407
April 8	0.2435	0.2777	0.0624	0.0694

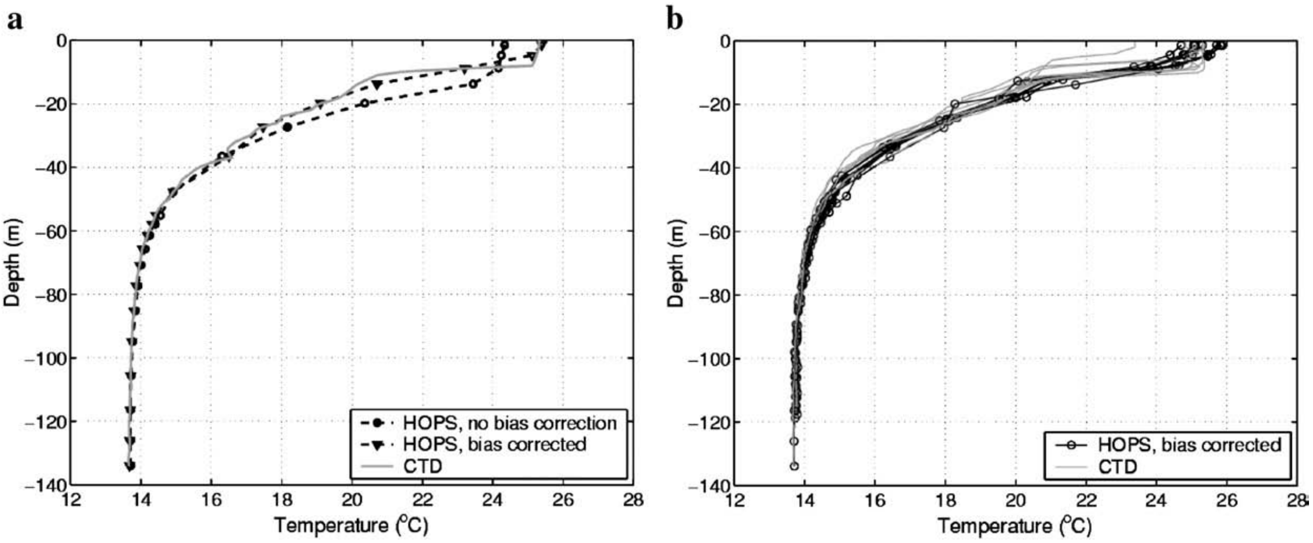

Fig. 10. a) one CTD profile (solid) taken on June 15, 2003, HOPS forecast — no bias correction (circles), HOPS forecast — after bias correction (triangles); b) second half of validation data set, observed profiles (solid), HOPS forecast — after bias correction (circles).

methodology if applied in real time. This process can also potentially lead to improved regional and sub-regional forecast ability for future exercises by illuminating modeling pitfalls to be avoided in those future modeling exercises. Fig. 10a demonstrates bias estimation from a single validation profile. A CTD profile taken on June 15, 2003, is compared with a 24-hour HOPS forecast for the same location. Fig. 10a presents the comparison before and after the bias correction. If this bias correction is considered as training the model, it can be applied to successive forecasts, as new validation data become available. Fig. 10b illustrates the improvement in forecast profile accuracy in the second half of the validation data set which results from training the bias correction model from the first half of the validation data set. Fig 11 further demonstrates that the bias correction training can be accomplished with as few as three or even one validation profile. Fig 11a shows bias corrected forecast profiles with a bias correction calculated from one profile only, while the Fig 11b demonstrates the results of learning via three profiles. Both training results indicate clear improvement in the HOPS forecast after training via bias correction. In real-time, the model could be corrected by using the first *in situ* cast, then the first three, then more as they become available. This model training is far less computationally expensive than running a suite of model simulations to test parameter choices and can be employed to correct

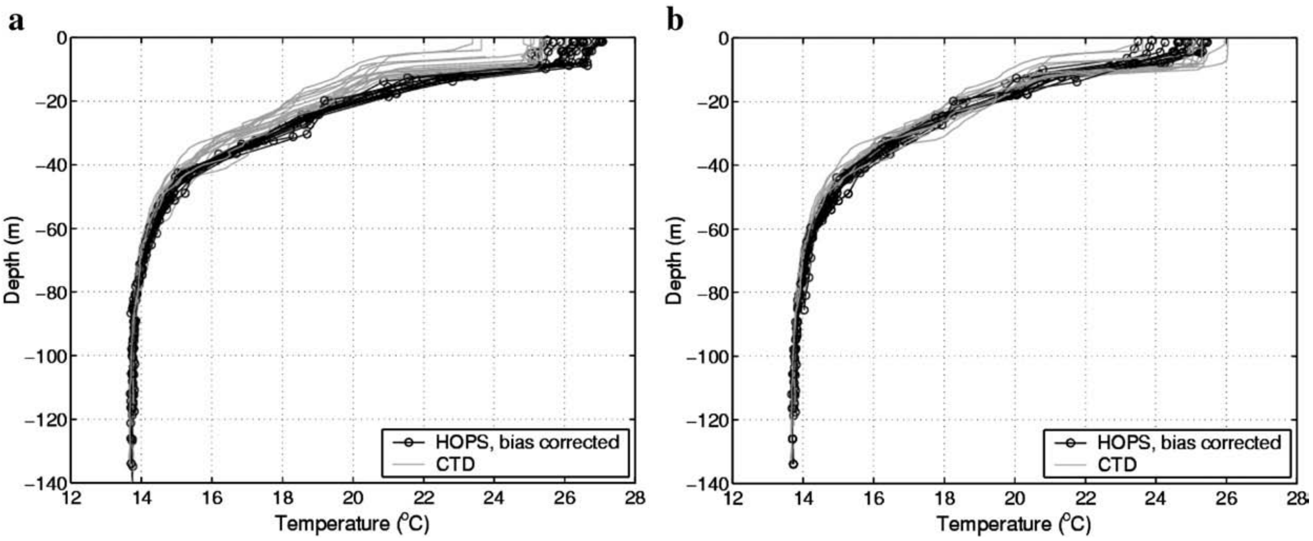

Fig. 11. Bias-corrected HOPS forecasted temperature profiles (solid) and observed profiles (circles) for 16 June 2003; a) bias correction from 1 profile; b) bias correction from 3 profiles.

forecasts during the course of real-time MREA operations. Of course, once exercise is completed, it is necessary to fix the model system to eliminate the most up-to-date bias by performing the type of re-calibration procedure illustrated previously for MREA03.

6. Conclusions

The forecasting of multi-scale ocean dynamics is a critical component of Maritime Rapid Environmental Assessment (MREA). The Harvard Ocean Prediction System provides real-time and hindcast, multi-scale oceanic field estimates for MREA. The calibration, verification and training of HOPS illustrated here are important components of the forecasting process. The potential now exists to adaptively forecast in real-time, thereby improving the multi-scale characterization of the environment, reducing forecast uncertainty, and better identifying, defining and characterizing local dynamics. These improvements will expand the usage and relevance of dynamical forecast-based MREA tactical decision aids.

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