Evaluation of sea surface temperature and heat flux in an assimilative Gulf of Mexico ocean model

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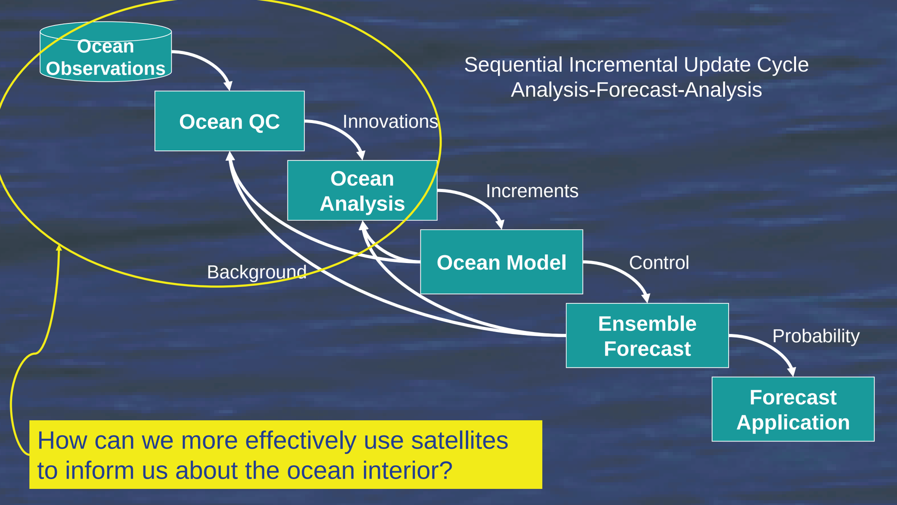
Abstract

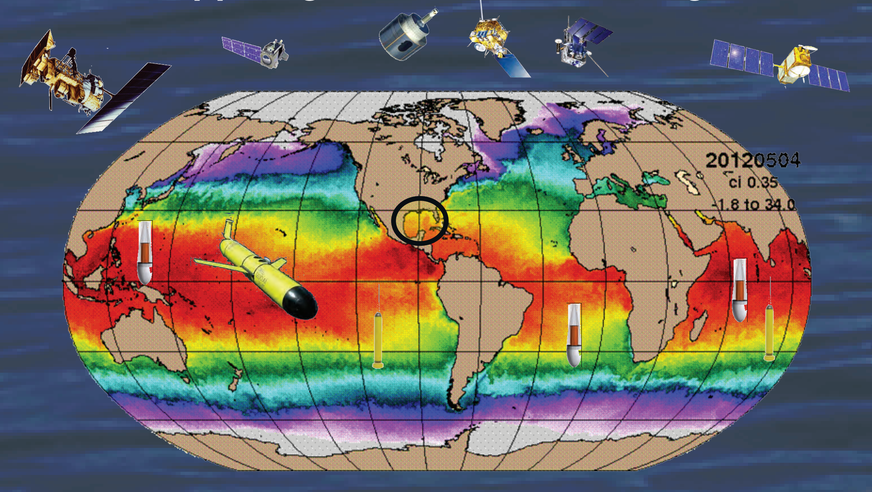
Variational assimilation of sea surface temperature (SST) guides analyses and forecasts toward agreement with measured conditions. 3DVAR assimilation assumes that forecast mismatches are due to errors in the initial state, while weak constraint 4DVAR balances assumed error levels in the initial state, lateral boundary conditions, model, observations, and forcing terms to best adjust the model trajectory. We examine the skill of forecasts from the Naval Coastal Ocean Model (NCOM) implemented in the Gulf of Mexico and assimilating various satellite observations. The impacts of various satellite data streams and alternative assimilation methodologies are evaluated by comparing model analyses and forecasts to unassimilated ship and buoy observations. Seasonal and diurnal trends in the forecast errors suggest biases in the heat flux which may be better addressed in a 4DVAR approach.

Components of an Ocean Prediction System



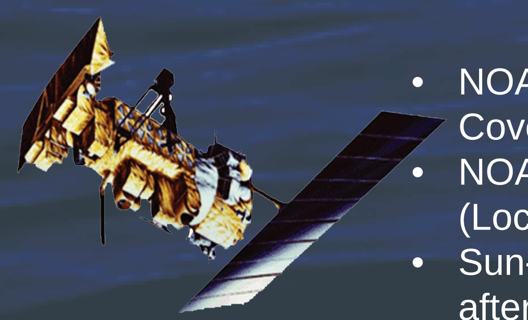
NRL 7320 seeks to develop advancements supporting ocean prediction systems

Satellite and *in situ* observations support global ocean modeling

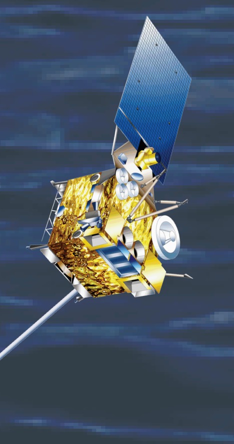


Ocean data assimilation guides the Global Ocean Forecast System (GOFS). Realistic model + data assimilation = accurate ocean forecasts.

Infra-red observations of Gulf of Mexico SST are available from the polar-orbiting NOAA and MetOp satellites and geostationary GOES



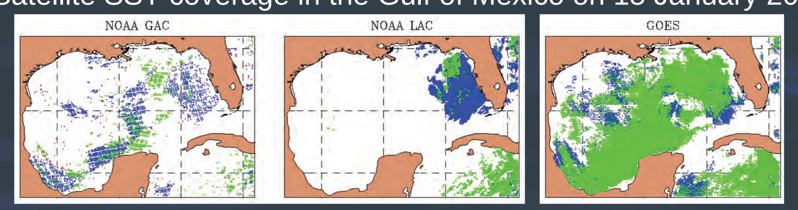
- NOAA 18 Global Area Coverage (GAC)
- NOAA 19 GAC and LAC (Local Area Coverage)
- Sun-synchronous, mid-afternoon orbits
- AVHRR/3 imager
- 1.1 km pixels, GAC processed to ~4 km at NAVOCEANO; 2 per day per satellite
- IR is obscured by clouds



- Geostationary Operational Environmental Satellite
- GOES 12 Jan-Apr 2010
- GOES 13 June 2010+
- Geostationary
- GOES Imager
- 4 km pixels, every 30 minutes
- SST processed by NAVOCEANO
- IR is obscured by clouds

Experiments on AVHRR vs GOES impact

Satellite SST coverage in the Gulf of Mexico on 15 January 2010.



- Gulf of Mexico Navy Coastal Ocean Model (NCOM) case studies assimilating
  1. AVHRR (GAC and LAC) and GOES
  2. AVHRR only, both GAC and LAC
  3. GOES only
- Run from 01 Dec 2009 – 31 Dec 2011
- Boundary conditions from GOFS 2.6; Forcing from COAMPS
- OCNQC ship observations are excluded from the assimilation data stream to serve as a basis for independent validation

Acknowledgements

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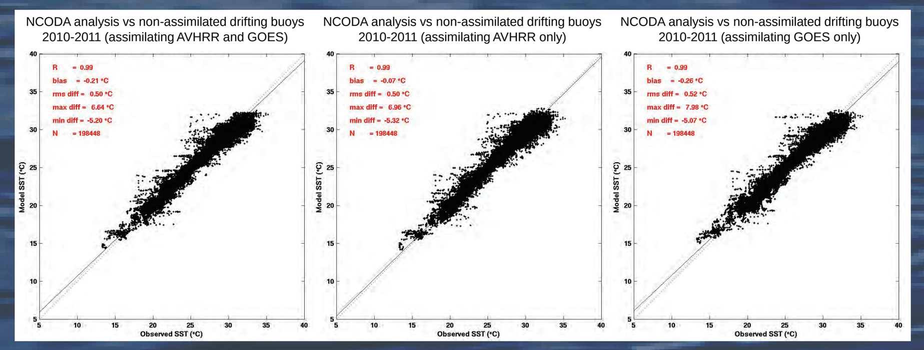
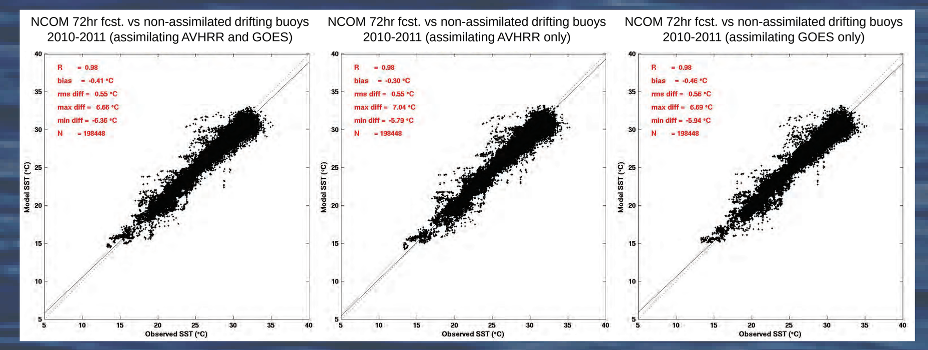
Evaluation of modeled SST relative to drifting buoy observations

NCODA Analysis



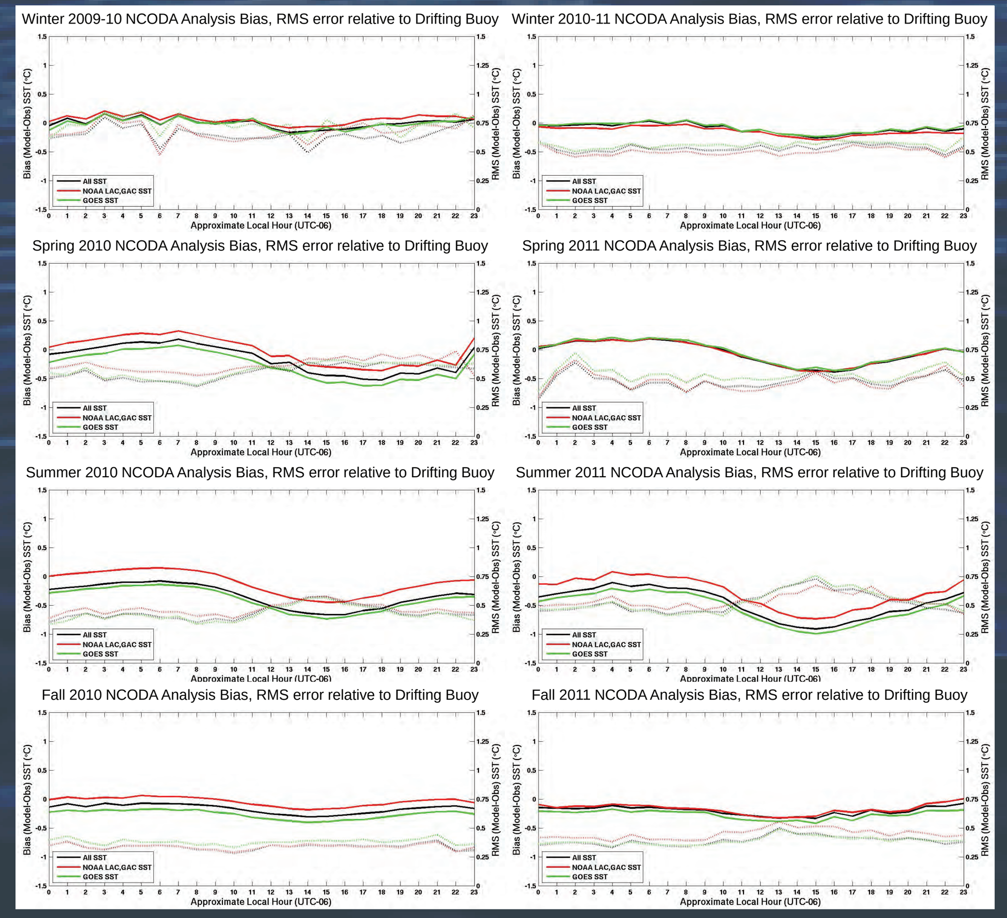
Assimilative (NCODA 3DVAR; Cummings, 2005; Smith et al., 2011) SST analyses cycling with NCOM forecasts are compared with independent, *in situ* SST observations in the Gulf of Mexico over 2010-2011. Matchups are interpolated linearly in time between daily 00:00 UTC analysis fields. SST biases from these cases are 0.07-0.26°C cold. The case relying solely on AVHRR SST has the bias closest to zero, while the case using only GOES SST has the coldest bias and largest RMS error. Assimilating both GOES and AVHRR leads to the smallest analysis RMS errors, 0.5°C. The cold analysis bias likely has its origin in the cold bias of the model forecasts that form the 3DVAR analysis background. The cooler GOES bias may indicate a larger fraction of undetected clouds.

NCOM 72-hour forecast



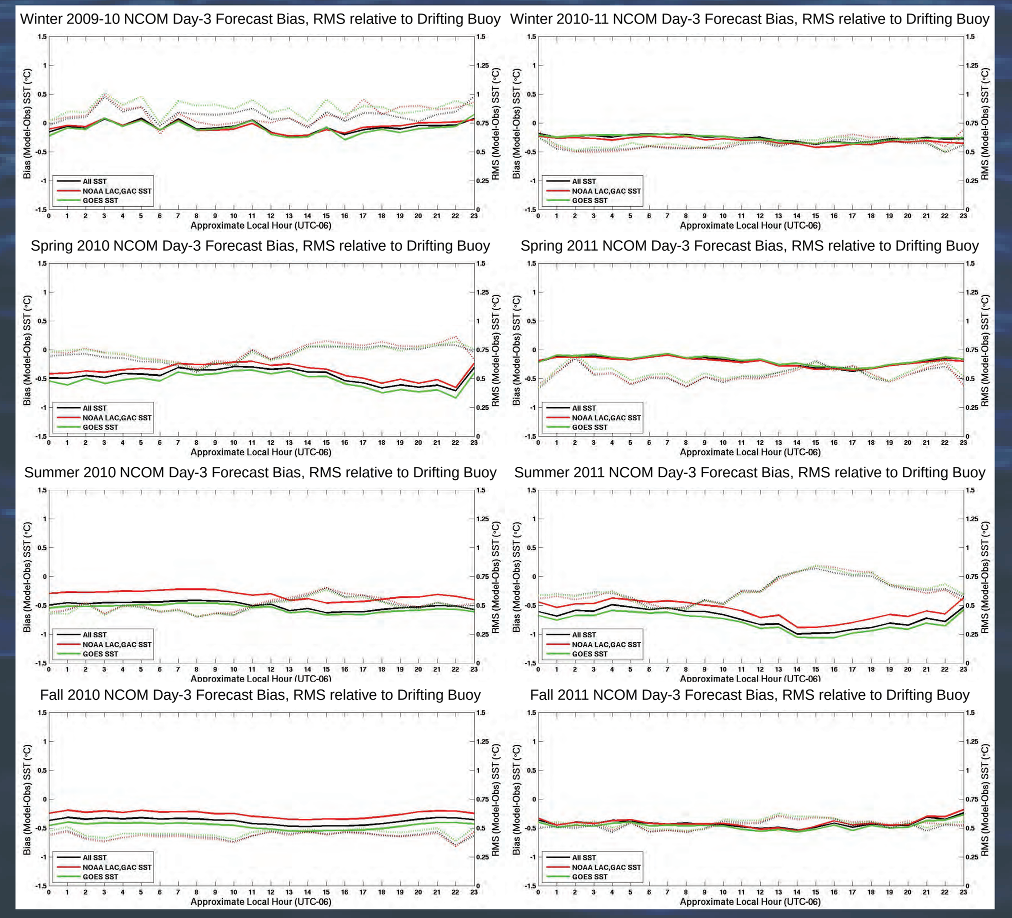
The day 3 (51-72 hr) NCOM (Barron et al., 2006) forecasts from 2010 through 2011 have a slight cool bias relative to independent OCNQC ship observations in the Gulf of Mexico. Matchups are interpolated linearly in time between 3-hourly forecast fields. The largest magnitude bias (-0.46°C) and largest RMS error (0.56°C) occur in the GOES-only case; the magnitude of the bias (-0.30°C) and RMS error (0.55°C) are smallest in the case assimilating AVHRR only, although the RMS error is unchanged when both GOES and AVHRR are assimilated. The present runs are based on 3DVAR adjustment of the model state at the analysis time. The cold forecast bias suggests that using 4DVAR assimilation might adjust the heat fluxes in addition to the model state.

NCODA Analysis bias (solid) and RMS error (dashed) vs local time of day (interpolated between daily 00:00 UTC analyses)



Matchups by local time of day are grouped by northern hemisphere season: winter, 21 Dec–20 Mar; spring, 21 Mar-20 Jun; summer, 21 Jun-20 Sep; fall, 21 Sep-20 Dec. Maximum analysis RMS errors of 0.75°C occur in the initial season, perhaps due to incomplete nested model spin up but also coinciding with operational changes adding NOAA-19 AVHRR and switching from GOES-12 to -13. RMS errors are 0.3-0.5°C over the remaining seasons, with smallest RMS errors in the fall. Spreads between the cases are largest in the summer and 2010 spring, with the AVHRR-only case having smallest bias. Biases are slightly cool, nearest zero when only AVHRR data are included, and coolest when only GOES data are used. Misidentified clouds in the satellite observations and a cold bias in the forecast 3DVAR background fields contribute to the cold analysis bias. Because the 00:00 UTC nowcasts align with local daybreak, they miss any diurnal warming. Mid-day to late afternoon biases are notably cooler, particularly in the spring and summer when diurnal warming is more evident. RMS errors are flat for most seasons but have a 2:00-4:00 PM maximum in summer.

Day 3 (51-72 hr) NCOM forecast bias (solid), RMS error (dashed) vs local time (interpolated from 3-hourly forecasts since 00:00 UTC)



The day-3 NCOM forecast comparisons show similar tendencies to the analyses. RMS errors are about 0.05°C higher, generally slightly above 0.5°C, with a seasonal maximum approaching 0.9°C in the winter of 2009-10. The most notable aspect of the forecasts is the cold bias. Analysis biases only fall below -0.3°C during summer afternoons when they miss significant diurnal warming. In contrast, day-3 forecast biases approach -0.8°C and are on the order of 0.2°C cooler than their analysis counterparts. Forecasts accurately represent the diurnal SST variations, with only a slight dip in the afternoon biases. The results suggest an overall underestimation of solar radiation, with the largest impact seen during the summer seasons of maximum warming. While the bias is closest to zero in the AVHRR-only case, the NCOM forecasts assimilating both AVHRR and GOES have the smallest RMS error. The combined observations cover the largest fraction of the domain, reducing divergence between the model and observed states. It appears that the increased coverage plays a more important role in improving skill than do any AVHRR/GOES differences.

SST statistics relative to *in situ* observations

Table of seasonal, annual SST comparisons relative to drifting buoy observations

SST Bias (°C)

		2009-10 winter	2010 spring	2010 summer	2010 fall	2010-11 winter	2011 spring	2011 summer	2011 fall	2010 annual	2011 annual	2010-11 mean
NCODA	AVHRR + GOES	0.00	-0.15	-0.32	-0.15	-0.08	-0.03	-0.44	-0.21	-0.24	-0.13	-0.21
	AVHRR	0.06	-0.01	-0.09	-0.03	-0.13	-0.02	-0.26	-0.18	-0.06	-0.12	-0.07
	GOES	-0.01	-0.26	-0.37	-0.25	-0.07	0.00	-0.52	-0.27	-0.31	-0.13	-0.26
NCOM day-3	AVHRR + GOES	-0.07	-0.46	-0.50	-0.37	-0.25	-0.19	-0.72	-0.43	-0.44	-0.32	-0.41
	AVHRR	-0.07	-0.37	-0.31	-0.25	-0.30	-0.20	-0.58	-0.42	-0.29	-0.32	-0.30
	GOES	-0.10	-0.54	-0.54	-0.46	-0.26	-0.17	-0.79	-0.47	-0.50	-0.32	-0.46

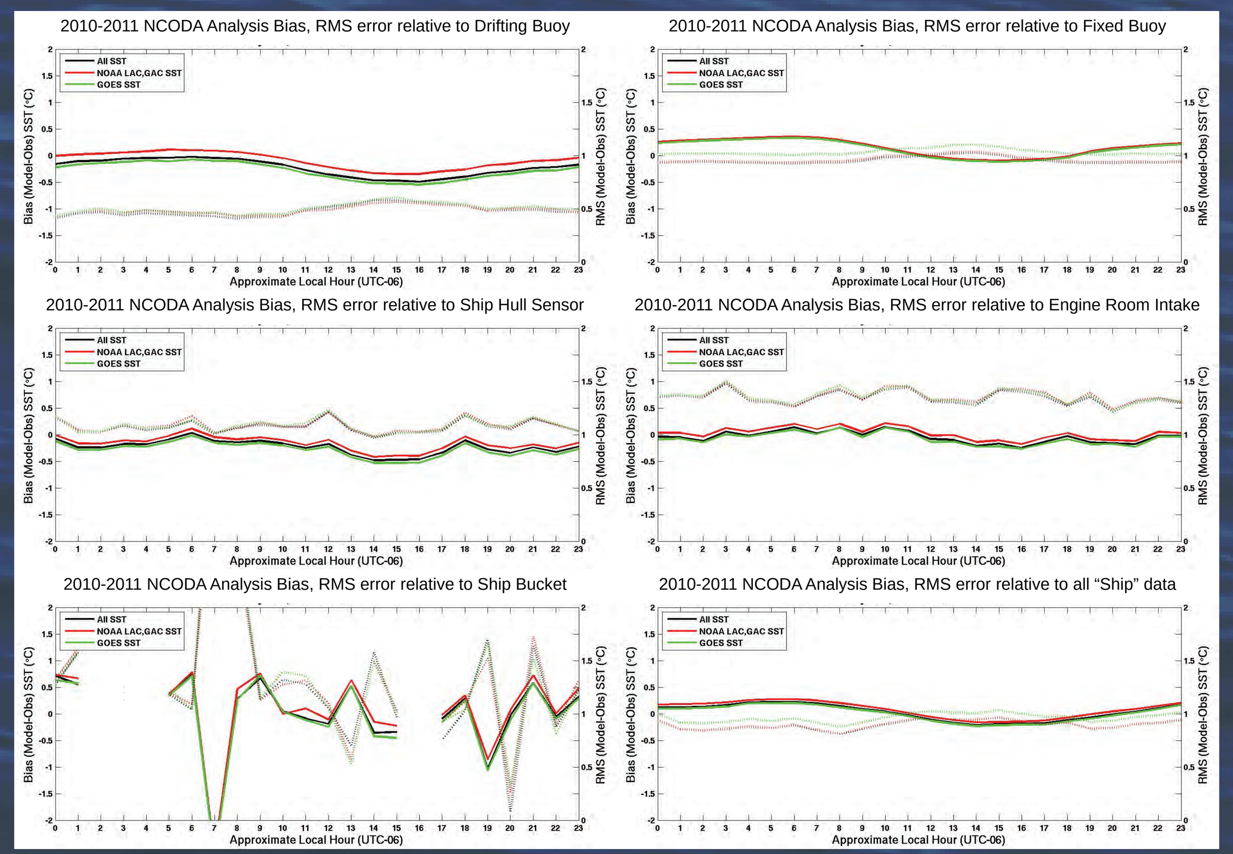
SST RMS (°C)

		2009-10 winter	2010 spring	2010 summer	2010 Fall	2010-11 winter	2011 spring	2011 summer	2011 fall	2010 annual	2011 annual	2010-11 mean
NCODA	AVHRR + GOES	0.65	0.60	0.48	0.35	0.53	0.52	0.58	0.40	0.47	0.56	0.50
	AVHRR	0.68	0.66	0.51	0.35	0.50	0.52	0.60	0.45	0.49	0.54	0.50
	GOES	0.74	0.62	0.47	0.39	0.56	0.57	0.59	0.40	0.48	0.59	0.52
NCOM day-3	AVHRR + GOES	0.82	0.72	0.50	0.44	0.55	0.54	0.64	0.52	0.53	0.60	0.55
	AVHRR	0.83	0.74	0.51	0.43	0.56	0.54	0.64	0.54	0.53	0.59	0.55
	GOES	0.89	0.73	0.49	0.46	0.57	0.56	0.64	0.54	0.53	0.63	0.56
number of drifting buoy matchups		4027	17764	77725	45052	24301	16461	8796	5046	147741	50707	198448

Tabular summary of SST statistics relative to drifting buoy observations. Independent drifting buoy observations provide between 4,000 and 50,000 observations for model-*in situ* data comparison. For the SST bias in each season, red identifies the case with the warmest bias and blue identifies the coldest bias. While all cases exhibit a cold bias, those relying solely on GOES tend to be colder while the AVHRR-only cases are closer to zero. RMS errors from both the analysis and forecast evaluations are smaller overall for cases including both AVHRR and GOES than for either of the single-sensor trials. Heat flux corrections to reduce the cold forecast bias will further reduce biases and RMS errors.

Drifting buoys and other sources of independent *in situ* SST observations

The biennial comparisons of NCODA analyses and various independent sources of *in situ* SST are shown to the right. The quality and distribution of the *in situ* SST measurements plays an important role in the reliability of SST validation statistics. Fixed buoys introduce a geographical bias that skew the results toward the high-frequency moored observations generally located very near the coast; the fixed buoy measurements outnumber those from drifting buoys 4 to 1, and thus skew the combined results as well. Other *in situ* measurements are relatively sparse: hull sensor and engine room intake provide 10-15% as many observations as the drifting buoys, while bucket temperatures number in the low hundreds, less than half of 1%. Relatively high measurement errors combined with a geographic bias toward shipping lanes render the latter three data types unattractive for assimilation or validation purposes. While the analysis matchups relative to the drifting buoys have RMS error below 0.5°C, comparisons to the other types and the combined sets have errors approaching or exceeding 1.0°C. These results support drifting buoys as the sole source of independent validating *in situ* SST measurements.



Conclusion

The cold forecast bias emerges as a key revelation from the SST evaluations in the Gulf of Mexico. Errors are largest in magnitude during midday to late afternoon, and bias is coolest in late afternoon, suggesting an underestimation of diurnal warming. In addition, biases are near zero in winter and coolest in summer. A possible source of these discrepancies is a low bias in the incoming solar radiation. A 6-hour update cycle or FGAT approach using GOES observations might reduce analysis errors but would be unable to address the forecast bias, as 3DVAR assimilation addresses only errors in the initial state. A 4DVAR approach that jointly mitigates errors in the initial state and boundary conditions holds more promise in these cases. Alternatively, other methods have been developed to calibrate or adjust surface forcing according to satellite measurements of the terms in the bulk heat flux formulation. Work at NRL is progressing along these avenues in addition to continuing work on incorporating the GHRSST (Gentemann, et al., 2009) data streams into the Navy ocean forecast systems.

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