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Electromagnetic bias estimation using in situ and satellite data: 1. RMS wave slope

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[1] The electromagnetic (EM) bias is the largest source of error in TOPEX/Poseidon and Jason-1 satellite altimeter sea surface height (SSH) estimates. Current operational EM bias models are based on empirical relationships between the bias, wind speed, and significant wave height. These models are limited in their accuracy because wind speed and wave height do not capture enough information about the sea state to uniquely specify the bias. In order to improve EM bias estimation, we have studied the correlation between the EM bias and RMS long wave slope using data from tower-based experiments in the Gulf of Mexico and Bass Straight, Australia. Models based on significant wave height and RMS slope are more accurate than models based on wave height and wind speed by at least 50% in RMS error between predicted and ground truth bias values. Furthermore, models which incorporate wave slope exhibit reduced regional variation between the two widely separated experiment locations. *INDEX TERMS:* 4275 Oceanography: General: Remote sensing and electromagnetic processes (0689); 4556 Oceanography: Physical: Sea level variations; *KEYWORDS:* EM bias, altimetry, RMS surface slope

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1. Introduction

[2] The dependence of nadir incidence backscattering coefficients for small surface facets on long wave surface displacement leads to an electromagnetic (EM) bias of up to tens of centimeters in altimeter measurements of sea surface height. Over time, the importance of this source of error has increased, as improvements in instrumentation and precise orbit determination have reduced other error contributions. Early satellite missions had altimetric and satellite positioning errors on the order of tens of centimeters. For the Jason-1 GDR data product, altimeter noise, orbit range, and propagation delay error budget contributions are respectively 1.7 cm, 2.5 cm, and 1.2–1.7 cm, whereas the total sea state surface height error budget contributes 4.2 cm, of which 3 cm is allotted to EM bias. As a result, EM bias estimation has continued to attract interest in recent years.

[3] Numerous studies on the EM bias have been conducted since its discovery by *Yaplee et al.* [1971]. Efforts to explain the theoretical mechanisms and physics that cause the EM bias have included laboratory experiments [*Branger et al.*, 1993; *Gommenginger et al.*, 2003], numerical analysis [*Glazman et al.*, 1996], and nonlinear sea surface models [*Elfouhaily et al.*, 2000, 2001]. Theoretical models have been of limited usefulness due to the difficulties inherent in modeling nonlinear ocean surface hydrodynamics and improving on approximate electromagnetic scattering models such as physical and geometrical optics. Because of this, operational EM bias estimation relies on empirical models. Current empirical models are based on significant wave height and wind speed measurements from the TOPEX/Poseidon satellite mission [*Gaspar et al.*, 1994; *Gaspar and Florens*, 1998; *Gaspar et al.*, 2002; *Chelton*, 1994]. Other models created from satellite data have accounted for wave development by including a wave age or pseudo-wave age parameter to improve the bias estimates [*Fu and Glazman*, 1991; *Rodriguez et al.*, 1992]. Empirical models have also been obtained from aircraft [*Hevizi et al.*, 1993] and tower experiments [*Arnold et al.*, 1995; W.K. Melville et al., Wave slope and wave age effects in measurements of EM bias, submitted to *Journal of Geophysical Research*, 2002 (hereinafter referred to as Melville et al., submitted manuscript, 2002)].

[4] The large amount of data collected from the TOPEX/Poseidon satellite have allowed very accurate models of the mean value of the EM bias to be created using crossover differences [*Gaspar et al.*, 2002]. Mean-bias models are limited by large variability of EM bias as a function of significant wave height and wind speed. The ultimate goal of current research efforts is to reduce this variability by including additional measurable or predictable parameters in bias models.

[5] The importance of hydrodynamic modulation in determining EM bias has been the subject of much study, especially in recent years [*Rodriguez et al.*, 1992; *Rozen-*

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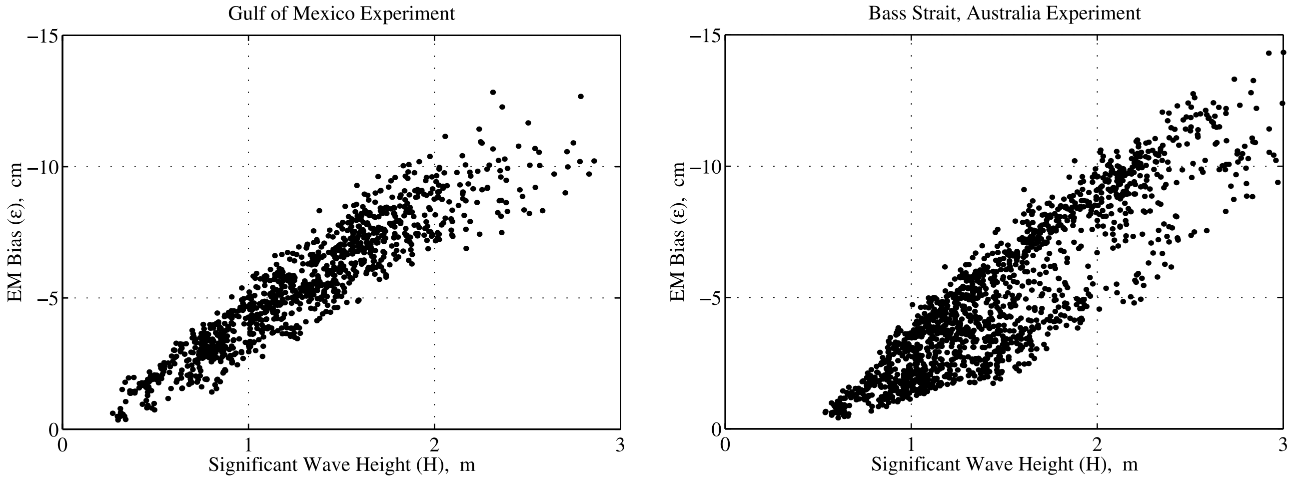

Figure 1. EM bias versus significant wave height. A strong linear correlation between the significant wave height and EM bias is evident.

berg et al., 1999; *Elfouhaily et al.*, 1999, 2001]. These theoretical studies indicate a relationship between EM bias and a higher order moment of the surface height power spectral density, such as RMS long wave slope, or a quantity that is closely related to a higher order moment, such as orbital velocity. In this paper, we study the correlation between the RMS long wave slope and the EM bias. We show that the wave slope is more strongly correlated to the EM bias than either wind speed or significant wave height. Due to the stronger correlation between the EM bias and the wave slope, the errors between measured and estimated values are significantly reduced relative to traditional wind speed and wave height models. The wave slope is also shown to create accurate estimates of the EM bias over different sea states, wind speed ranges, and locations.

2. Data Sets

[6] One of the difficulties in creating EM bias measurements using remote sensing instruments is the lack of measured truth values. Previous EM bias studies have used a variety of methods to obtain accurate estimates. *Gaspar et al.* [1994] and *Chelton* [1994] used cross-track or colinear estimation techniques, respectively, to create EM bias estimates from satellite data. *Hevizi et al.* [1993] used laser measurements in their airplane experiments to collect the data necessary for EM bias estimation.

[7] The tower experiments of *Arnold et al.* [1995] in the Gulf of Mexico (GME) and Melville et al. (submitted manuscript, 2002) in the Bass Strait, Australia (BSE) [*Melville and Felizardo*, 1998; *Melville and Matusov*, 1999] created direct measurements of the EM bias. Each experiment used a Ku-band altimeter to measure the apparent sea surface height. Concurrent measurements of the ocean surface were made using wave gauges. The EM bias was then calculated as the difference between the measured and apparent sea surface heights. Simultaneous measurements of the wind speed were also made.

[8] In agreement with past experiments, the GME and BSE data sets show a roughly linear relationship between the significant wave height H and the EM bias, as shown in Figure 1. As is commonly done, we remove the leading linear dependence on H and study the normalized EM bias,

$$\beta = \frac{\epsilon}{H}. \tag{1}$$

Thus, the models studied in this paper are of the form

$$\epsilon = a(U, H)H, \tag{2}$$

where $a(U, H)$ is a normalized bias model and U is wind speed referred to a 10 m height. Since values for the significant wave height typically range from 0.5–3 m for these data sets, a value of 1% of the significant wave height for the normalized bias ranges from 0.5–3 cm. After this point, we will refer to the normalized EM bias as EM bias, for brevity.

[9] It will be seen that GME and BSE data sets show similarities that can be attributed to general traits in the oceans of the world as well as specific regional characteristics. The data sets are combined to form a third data set, referred to as TOT. The relationships between the models created from the three data sets are used to identify regionally applicable characteristics as well as the general features that are applicable to global EM bias estimates.

3. RMS Long Wave Slope and Hydrodynamic Modulation

[10] Studies of the relationship between scattering from the ocean surface and hydrodynamic modulation have been an active area of research in recent years. A number of results have provided strong empirical and theoretical support for the importance of hydrodynamic modulation as a determinant of the EM bias [*Rodriguez et al.*, 1992; *Rozenberg et al.*, 1999; *Elfouhaily et al.*, 1999, 2001]. Because of the difficulty of solving the nonlinear equations which govern sea-air interactions, a number of approaches to parameterizing hydrodynamic modulation have been suggested. Most treatments involve higher order moments of the surface height power spectral density. Surface slope variance has long been suggested as a candidate for including the effects of hydrodynamic modulations in EM bias models, on both empirical

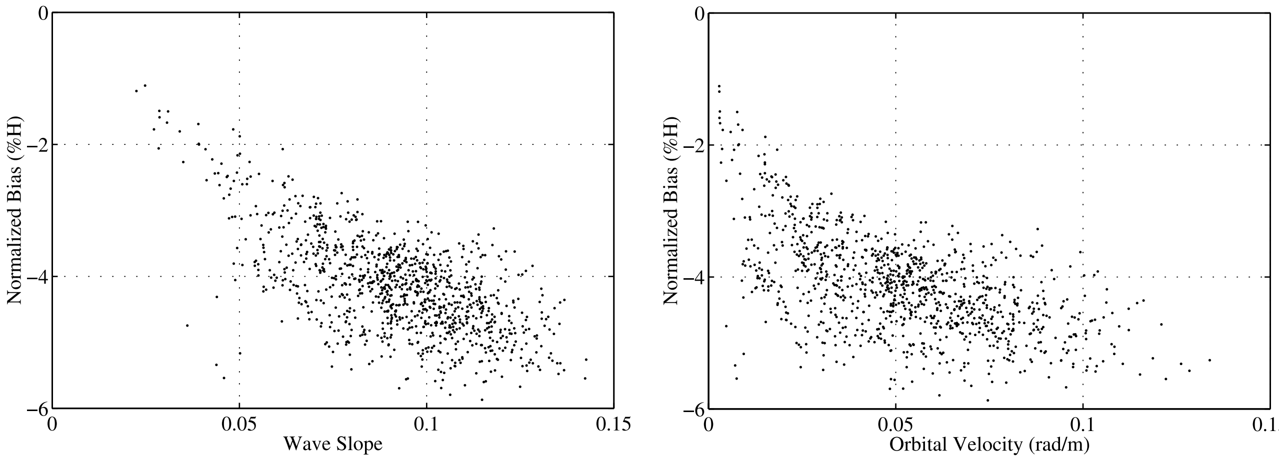

Figure 2. Normalized bias versus RMS wave slope and normalized bias versus orbital velocity. The RMS wave slope and orbital velocity are similar in their correlation with the normalized bias.

and theoretical grounds [*Rodriguez et al.*, 1992]. Later studies lend further support to the importance of surface slope [*Gommenginger et al.*, 2003]. Indeed, a simple computation based on a two-scale surface model and nonlinear hydrodynamic theory shows that to first order, the change in amplitude with displacement of small waves riding on long waves is in direct proportion to RMS long wave slope S (W.K. Melville, personal communication, 1999),

$$\frac{a(\eta)}{a(0)} \simeq 1 + \sqrt{2}S\eta/a_l, \tag{3}$$

where η is surface displacement due to a long wave of amplitude a_l. These considerations motivate the use of RMS slope in this paper.

[11] Instead of slope variance or RMS surface slope, which can be obtained from the second moment of the surface height power spectral density, EM bias dependence on orbital velocity has also been studied theoretically [*Elfouhaily et al.*, 2001]. Orbital velocity can be related to the first moment of the surface height power spectral density (PSD). The dependence of EM bias on orbital velocity has also been studied using the tower data reported in this paper. In fact, Figure 2 shows that the correlation between normalized EM bias and RMS wave slope is similar to that of orbital velocity. A more detailed comparison shows that models based on wave slope performed slightly better than models using orbital velocity. As the difference between both sets of models was slight, however, the results cannot be considered to support RMS slope over orbital velocity, but rather demonstrate that inclusion of some parameter related to a higher moment of the surface height PSD leads to models that perform significantly better than those based only on significant wave height and wind speed.

[12] There is good reason for the similar correlation of EM bias with RMS slope and orbital velocity. To improve bias models depending only on significant wave height and wind speed, additional model parameters must include information not available from these two parameters. Significant wave height is dominated by the longest surface wave components at wavenumbers much lower than the EM wavenumber. Instantaneous wind speed determines the amplitude of capillary wave components with very high wavenumber, on the order of the EM wavenumber. Higher order moments of the surface height PSD tend to emphasize surface components near a cutoff frequency which is generally chosen to be less than the EM wavenumber and larger than the wavenumber of the longest waves. Thus, RMS slope and orbital velocity contain information about midrange surface waves, smaller in wavelength than those represented in the significant wave height and longer in wavelength than Bragg-scale capillary waves driven by local winds.

[13] Because surface height measurements in the BSE and GME experiments were performed in time but at the same spatial point, the surface height wavenumber PSD is not directly available. Well-known and commonly used techniques allow the RMS surface slope to be obtained from the time frequency PSD, $W(\omega)$, instead. *Cox and Munk* [1956] obtain the result

$$S = \left[\int k^2 W(\omega) d\omega\right]^{1/2}, \tag{4}$$

where k is given by the surface wave dispersion relation

$$\omega^2 = gk + \gamma k^4. \tag{5}$$

Here, γ is the ratio of surface tension to density and g is the acceleration due to gravity. Since we are interested in medium to long wave surface components with wavelength on the order of 1 m or longer, we neglect the second term of equation (5), since it is significant only for capillary waves of centimeter-scale and smaller. Discretizing the integral in equation (4) using an N-point Euler quadrature rule and making use of the dispersion relation leads to

$$S = \left[\Delta\omega \sum_{n=1}^{N_c} \frac{\omega_n^4}{g^2} W(\omega_n)\right]^{1/2}, \tag{6}$$

where $\Delta\omega = \omega_{max}/N_{FFT}$, ω_{max} is the maximum time frequency at which the N_{FFT} PSD is computed, and N_c corresponds to the upper cutoff frequency, ω_c. For the GME experiment, the sampling rate of surface height measurements is 8.2 Hz.

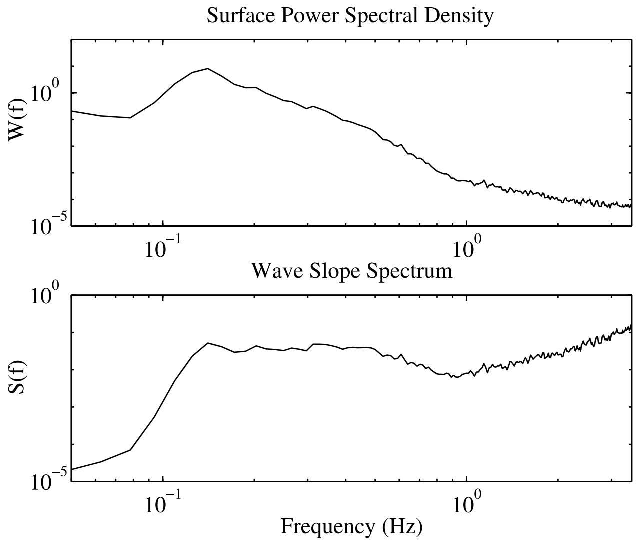

Figure 3. Typical 1-hour averages of the surface height power spectrum, $W(f)$, and slope spectrum $S(f)$.

[14] One of the chief difficulties in determining a meaningful RMS long wave slope is an appropriate choice of a cutoff frequency for the surface height displacement spectrum. For both the GME and BSE tower experiments, the radar footprint was small enough that each instantaneous backscatter measurement can be considered to be due to a single facet consisting of small, Bragg-scale waves tilted and modulated by longer waves. Thus, the long wave surface components could be considered to consist of wavelengths longer than the radar footprint. Using the gravity wave dispersion relation, this leads to a long wave cutoff frequency of roughly 1 Hz. Figure 3 shows that the typical time frequency surface spectrum deviates from the expected power law trend near 1 Hz. To avoid this region, the cutoff frequency for both experimental data sets was chosen to be f_c = 0.8 Hz.

[15] The mean RMS slope values for the GME and BSE experiments differed by a small factor. Because the raw data for the BSE experiment was not available, the RMS slope values could not be recomputed using identical processing, so the GME slope values are multiplied by a factor of 0.67 to coregister the two data sets.

4. Qualitative Analysis

[16] After the removal of the linear relationship between the EM bias and the significant wave height, it can be seen in Figure 4 that the normalized bias is only weakly correlated with the significant wave height in either experiment. The second-order polynomial, least squares estimates in the plots also show that the fit to significant wave height is not consistent across the two experiments. The form and the zero significant wave height intercept of the estimates show large discrepancies.

[17] Figure 5 shows a more strongly correlated relationship between the wind speed, U, and the normalized bias. The plots show more regional correlation between the GME and BSE experiments, but as with the second order fit to H, the zero wind speed intercepts are significantly different for the two data sets.

[18] Of the three parameters studied, the normalized EM bias is the most strongly correlated to RMS long wave slope, as seen in Figure 6. Although the improvement is less pronounced for the GME experiment, there is less scatter associated with the wave slope than with either wind speed or significant wave height for both data sets. The shape of the estimates is more consistent from one data set to the other, indicating that wave slope may explain regional variability in the EM bias. As with the significant wave height and wind speed second-order fits, the intercepts for fits to slope are also different for the two models. It is clear from inspection of the data sets, however, that the trend for low slope values for both experiments is towards a very small or zero intercept value that is nearly identical in both cases.

5. Methodology

[19] The general form of the EM bias models considered in this paper is

$$\beta = a_0 + \sum_{i=1}^{N} a_i P_I, \qquad (7)$$

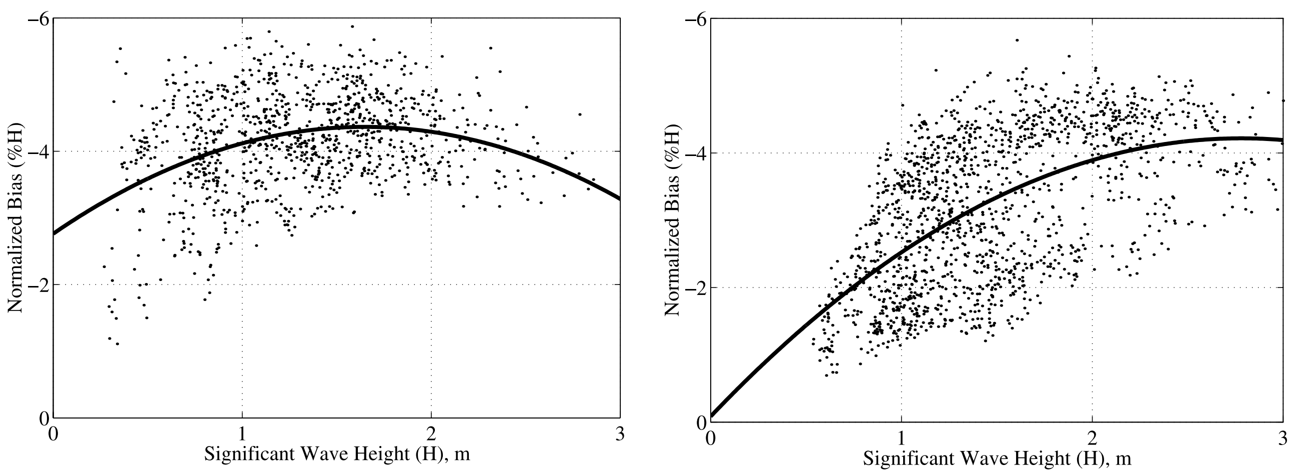

Figure 4. Normalized bias, β, versus significant wave height, H, showing a second-order least-squares fit to the data.

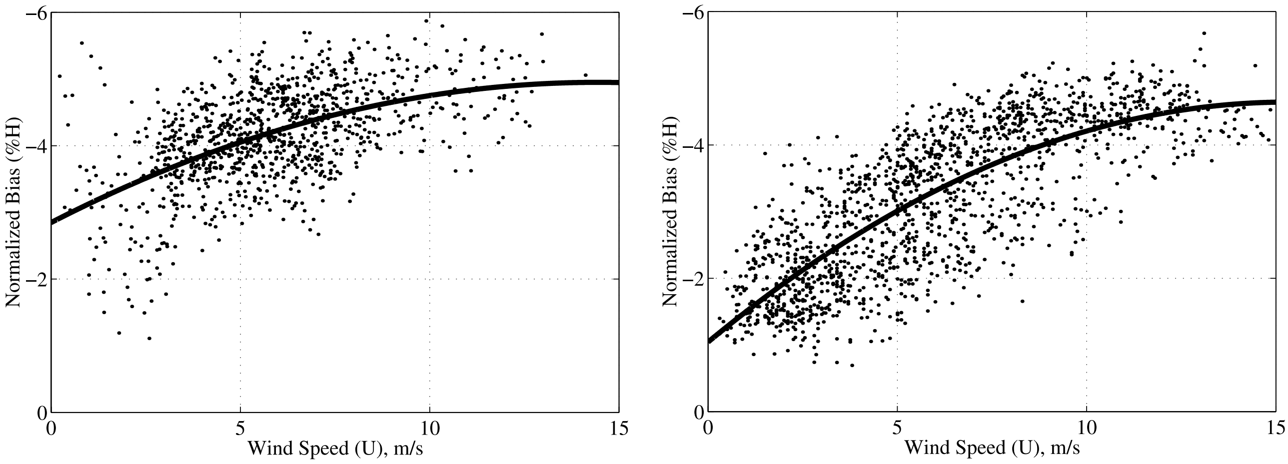

Figure 5. Normalized bias, β, versus wind speed, U, showing a second-order least-squares fit to the data.

where β is the normalized bias, N is the number of terms in the model, and P_i is a linear or second-order term in the Taylor series expansion of $a(U, H, S)$, so that P_i is chosen from the set U, H, S, U^2, H^2, S^2, UH, US, or HS. Writing the coefficients a_i in equation (7) in vector form $\vec{a}$ and minimizing the RMS error of the model over a data set leads to the least squares solution

$$\vec{a} = \left(\vec{P}^T\vec{P}\right)^{-1}\vec{P}^T\vec{\beta}, \tag{8}$$

where $\vec{P} = [1, P_1, \ldots, P_N]^T$ and $\vec{\beta}$ is a vector of measured normalized bias values.

[20] By subtracting estimated values from measured values over a data set, a vector of error values is created. These are referred to as residual errors. The metric used in determining the most effective models is the RMS value of the residual errors. This approach to determine the optimal combination of parameters is similar to that of *Gaspar et al.* [1994]. Models are created for each of the three data sets: GME, BSE, and TOT. These models are used to estimate each of the data sets. Residual errors are calculated and the models ranked according to the RMS residual error. Best-case models are also created for each of the data sets, with and without the wave slope parameter.

6. Results

6.1. One-Term Models

[21] One-term models are defined to be of the form

$$\beta = a_0 + a_1 P_1, \tag{9}$$

where P_1 is one of the parameters U, H, S, U^2, H^2, S^2, UH, US, and HS.

[22] The plots in Figure 7 show RMS error values for the differences between the measured normalized bias values and the one-term models indicated. Each of the plots shows the models for a given data set: GME, BSE, or TOT. The parameters on which the models are based are ordered for monotonically increasing RMS error values for the TOT data set.

[23] The best one-term models of the normalized bias for each data set are created using the wave slope data. The BSE normalized bias values are seen to be especially well correlated with the S. Other terms which have contributions from the wave slope are also seen to be more highly

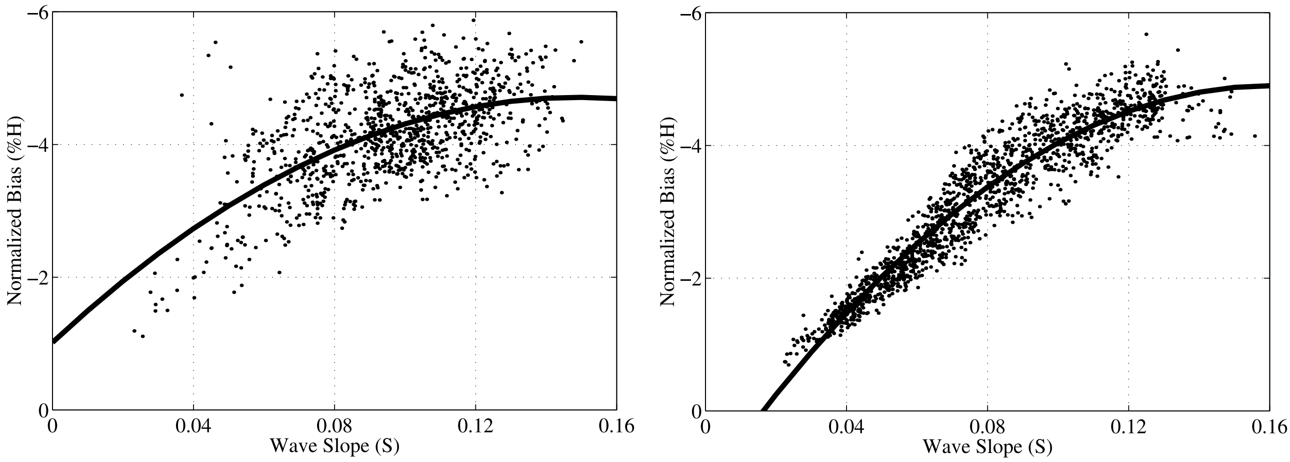

Figure 6. Normalized bias, β, versus wave slope, S, showing a second-order least-squares fit to the data.

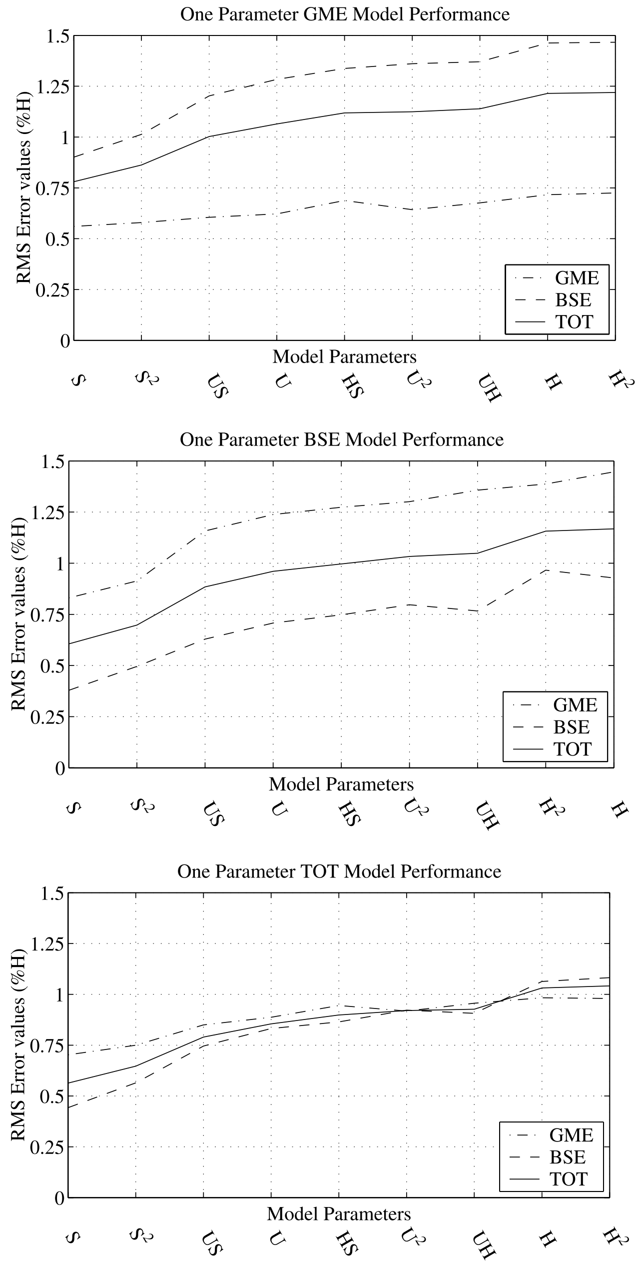

Figure 7. One-term model performance. The wave slope, *S*, generally provides the best models, while the significant wave height, *H*, carries the least amount of information on the normalized EM bias.

correlated to the normalized bias. To calculate the normalized bias, the linear dependence on *H* is removed. The one-term models show that there is much less bias information remaining in *H* than that contained in *U* and *S*. This is seen in Figure 7 by models containing contributions from *H* having the largest error values. Models containing wind speed information are more strongly correlated to the normalized bias than models based on *H*, but generally have larger RMS error values than models using *S*.

6.2. Two-Term Models

[24] Two-term models provide significant improvement over the one-term models. For every combination of model and data set, the top two-term models significantly outperform the best one-term model. There is also a shift in the importance of the various parameters when two terms are used. The one-term models identified the wave slope and the wind speed as the parameters which contain the most information individually.

[25] The two-term models identify the combination of parameters which contain complementary information. Figure 8 shows that the models with lowest error values are derived from terms containing *S* and *H*. Though *U* contains

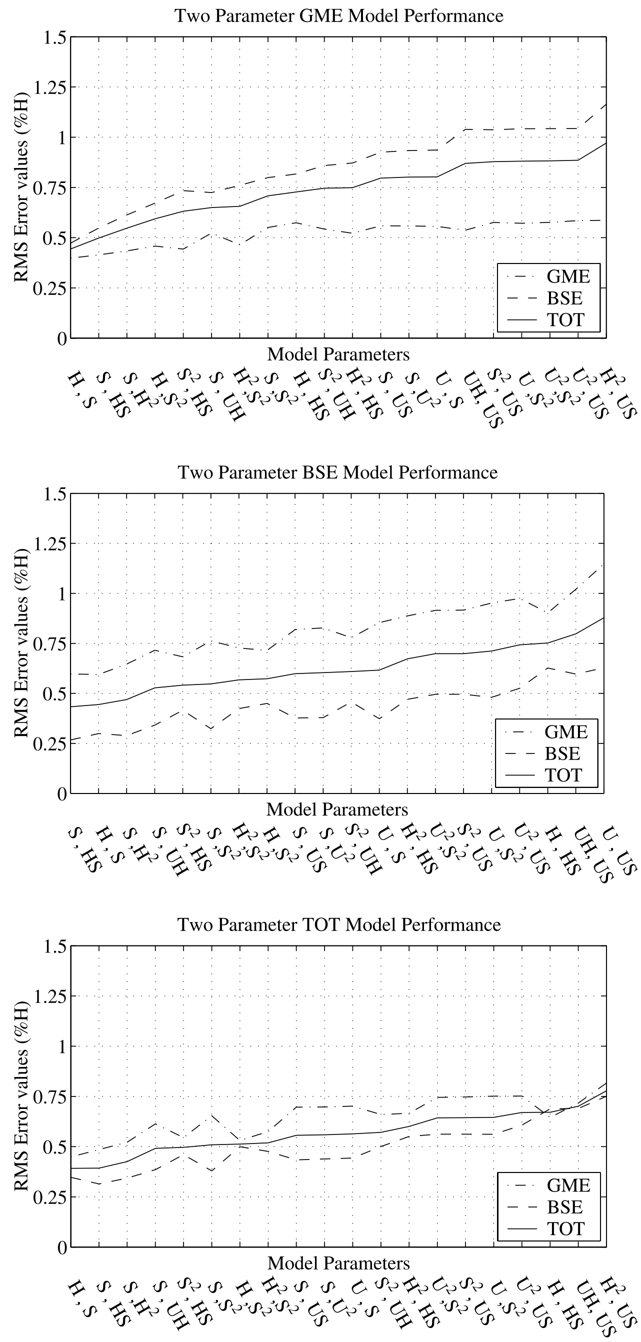

Figure 8. Two-term model performance. The best models show the complementary information that the wave slope, *S*, and significant wave height, *H*, parameters use to create more accurate models.

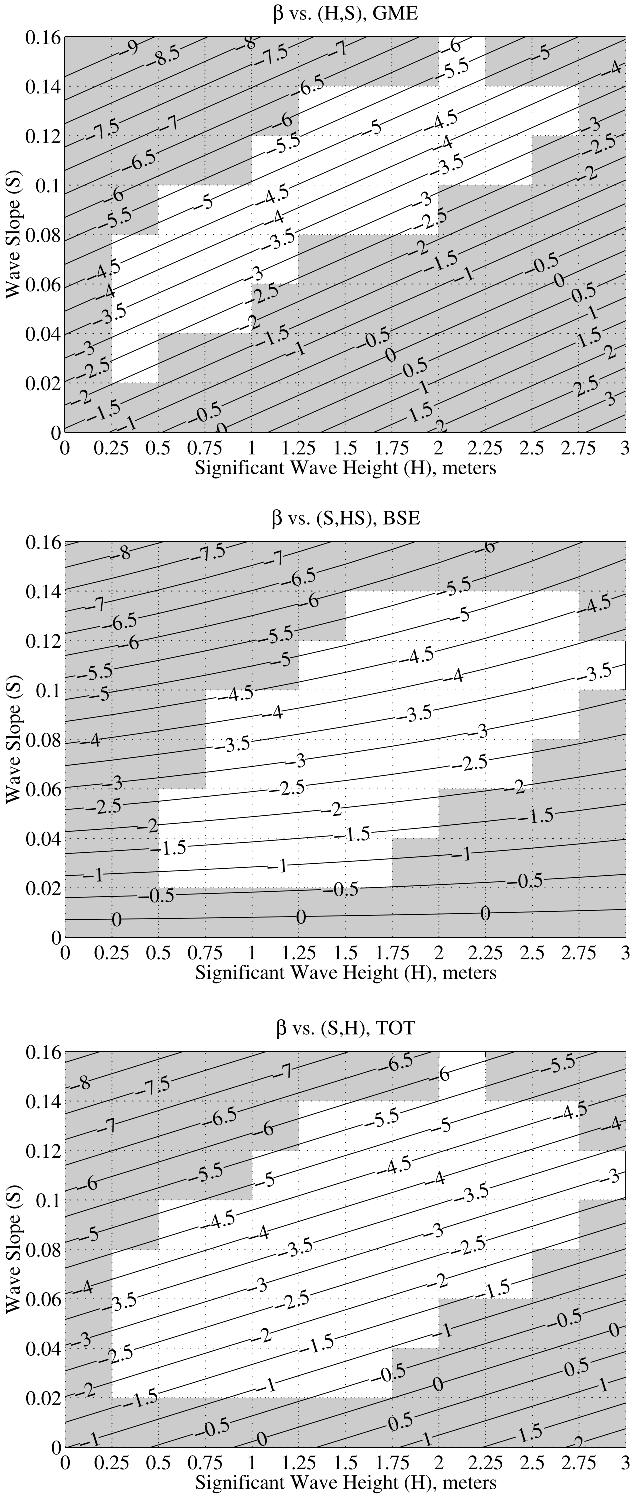

Figure 9. Best two-term models for each data set. When estimating the TOT data set, the terms in the best models are composed solely of the wave slope and significant wave height. Shaded areas indicate regions with no data.

more information on the normalized bias than *H*, the two-term models indicate that it is redundant information to that contained in *S*. Conversely, the information contained in the *H* and *S* terms is complementary. Combinations of terms derived from *S* and *H* constitute the best five models in every case. The best two-term models for each data set are shown in Figure 9.

6.3. Three-Term Models

[26] The 20 three-term models with the lowest RMS errors from each of data set is shown in Figure 10. The addition of a third term to the normalized bias models results in improvement over the two-term models on the order of 0.1% of the significant wave height. In addition, the differences in the RMS error values among the top three-term models is very small. Much of this is due to the

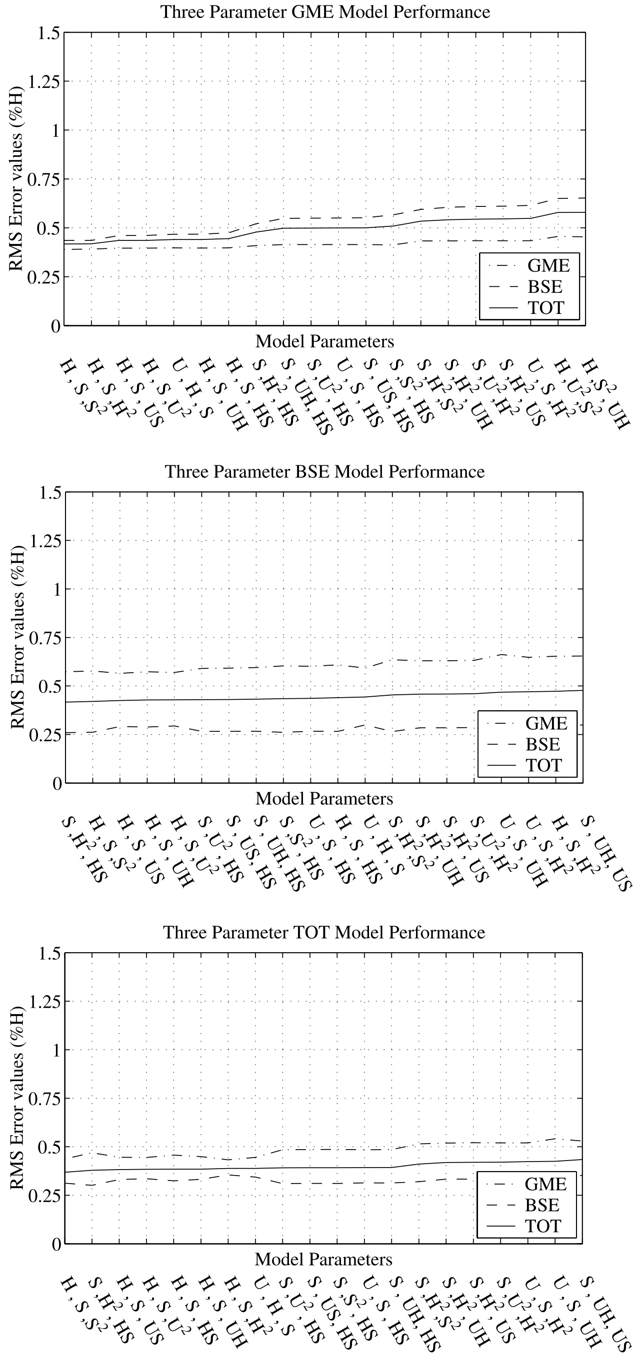

Figure 10. Best three-term model performance. The best models are predominantly derived from the wave slope, *S*, and significant wave height, *H*, parameters.

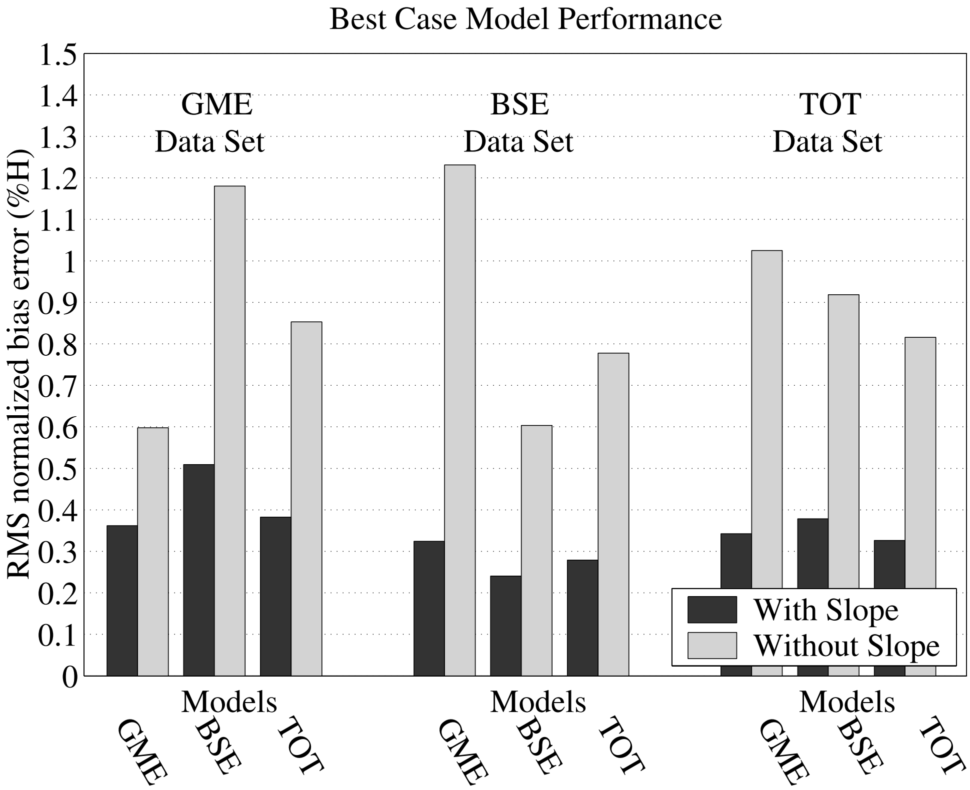

Figure 11. Residual errors for best-case models. The models derived using the wave slope show error values that are significantly smaller than those models that use only wind speed and significant wave height.

most accurate models relying on the same terms. It can be seen that the wave slope *S* is included in the best 10 models regardless of the data set from which the models are created.

6.4. Best-Case Models

[27] Models created with more than four terms resulted in very slight improvements in some cases, and in many cases the RMS error values increased. For all cases the RMS error values for the four-term models were within 0.012%*H* of the best model for that combination of model and data set. The best four-term models were consistently those including the terms S, H, H^2, and HS.

[28] For comparison purposes, the best models for each of the combinations of models and data sets were created without using the *S* parameter. The Taylor series expansion for these models yields five terms: U, H, U^2, H^2, UH. Figure 11 shows the results of these models and the best-case models using *S*.

[29] The models including the wave slope parameter have RMS error values that are better by over 50% in every case but one, and every case shows improvements of at least 0.23%*H*. For the more general TOT model, the improvement is over 0.5%*H* regardless of the data set to which it is applied.

7. Residual errors

[30] Figure 12 shows the residual errors for the best one-term, two-term, three-term and best-case models for the TOT data set. The vertical line on the graph indicates the break between the GME and the BSE data. The x-axis is a chronological ordering of values, with each point representing a 10-min average. Due to spurious data points in the two experiments, there are jumps in the data sequence, so that the horizontal axis is a pseudo-time representation of the data.

[31] It can be seen from these figures that the residual plots show some remaining correlation in time. As the number of terms increases, not only do the errors decrease, but the correlation can be seen to decrease as well. However, even for the best-case model with slope, there are indications that the errors are correlated and show some time-dependent physical property of the wave field. Future research should investigate the cause of this correlation.

8. Conclusion

[32] This study investigated the improvements in EM bias estimation using the RMS wave slope parameter. Measurements from the Gulf of Mexico Experiment (GME) and the Bass Strait, Australia Experiment (BSE) show regional differences in the wind speed and significant wave height parameters. The correlation of the EM bias with these parameters exhibits significant variability. Due to these characteristics, models based on the wind speed and significant wave height result in large residual errors when compared with truth data. Including RMS long wave slope as a model parameter reduces estimation error across a wide range of wind and sea conditions. The improvement in

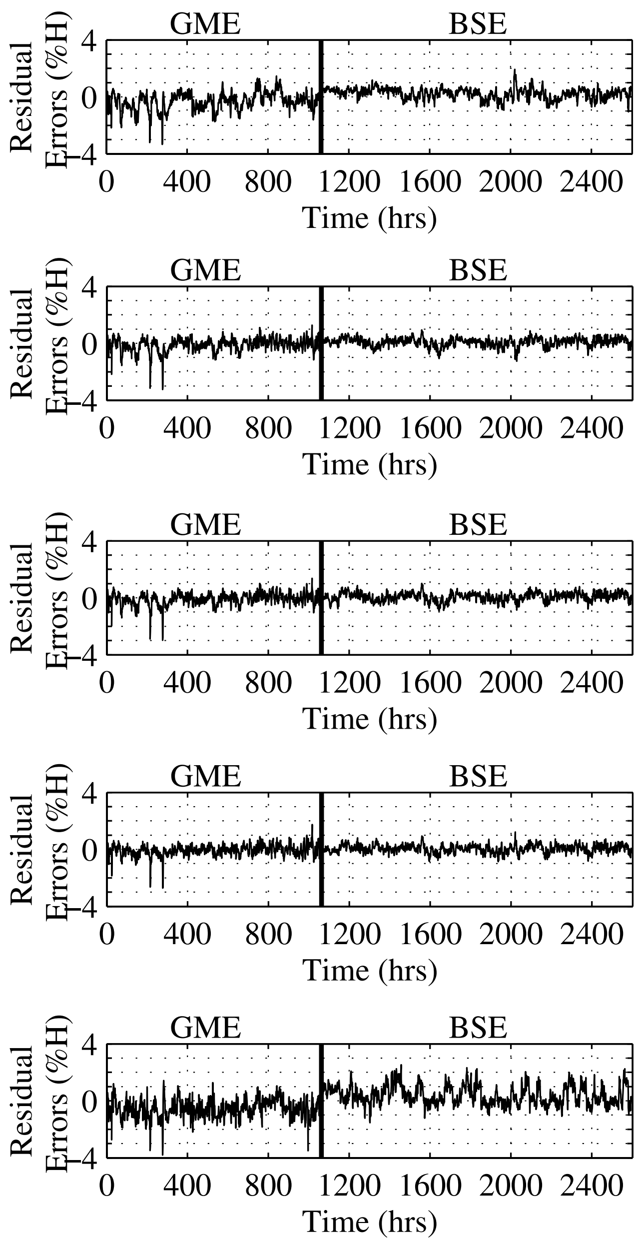

Figure 12 Residual error values for the best 1- to 4-term TOT models using wave slope and the best TOT model that does not use wave slope.

model correlation was evident over a variety of models based on various combinations of wind speed and significant wave height. Models based on wave slope also reduced the regional variability of the models when the two experimental data sets from widely separated locations were combined. Slope-based models also improved cross-estimation of one data set using a model based on the other set. Typical improvements over wind speed and significant wave height-based models were on the order of 50% as measured by RMS error between predicted and truth EM bias values.

[33] The information provided by the wave slope was also shown to be complementary to the significant wave height. Models based on combinations of the wave slope and significant wave height consistently resulted in the smallest error values between the measured and estimated bias values relative to models which included wind speed. RMS residual bias errors for these models were on the order of 0.34%*H*.

[34] As satellite altimetry instrumentation improves, the gains to be realized by improving EM bias estimates become increasingly important. Future satellite missions may have EM bias error budget contributions on the subcentimeter level. Models based on the RMS long wave slope improve estimation errors to essentially this level. These results will obtain operational value if a means can be found to obtain remotely the wave slope or another sea-state parameter such as orbital velocity containing similar information on hydrodynamic modulation. Various means have been suggested for accomplishing this, including detailed studies of altimeter return signal waveforms and predictive wave models based on wind history, but conclusive results along these lines await further work.

[35] **Acknowledgments.** We would like to express appreciation to Ken Melville for helpful conversations as this work has progressed and for generously allowing us to use the Bass Straight Experiment data set.

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