CONNECTING SEA LEVEL FORECASTS WITH THE BULK EXPORT INDUSTRY

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ABSTRACT

This study summarises the benefits of improving sea level forecasts for use in port operations from a shipping perspective. Maturation of operational sea level and ocean surface anomaly forecast services have provided the opportunity to utilise the skill that they offer to improve logistical operations at bulk goods terminals where short term Under Keel Clearance (UKC) are paramount to efficiency and safety.

OMC International has been collaborating with the Bureau of Meteorology to evaluate the applicability of the OceanMAPS aggregate sea level forecasts that have now transitioned to an ongoing operational service. The development work to evaluate the forecasts was carried out on an experimental development version. The approach developed has proven to have the ability to utilise the improved accuracy of the new model.

Furthermore, the availability of water level anomaly forecast models from other providers potentially offer non-correlated skill which can be incorporated into the model in an ensemble consensus style of assimilation. The different forcing sources, physical models and calculation architecture will be explored to understand the potential of combining heterogeneous numerical model forecasts in an operational setting. To that end, MetOcean Solutions Ltd have also provided operational water level forecasts to validate this hypothesis.

This study outlines a stochastic framework for incorporating forecasts from multiple sources to maximise the benefits for the end user, foremost with the particular needs of deep draft vessel import and export shipping.

Keywords: Water level, sea, tide, shipping, ports

1 INTRODUCTION

Bulk trade through bulk export ports can benefit from optimised vessel drafts derived from forecasts of environmental processes such as ocean swells and water levels, and thus improve cargo throughput.

In this paper, OMC International aims to utilise existing sea level forecasting to cater to the needs of bulk port operations from an under-keel clearance perspective. We will present a new approach that incorporates numerical forecasts with in-situ environmental observations on an operational basis.

A good prognosis of water level allows operators to maximise the amount of cargo carried on each ship while maintaining safe vertical clearances. Every extra centimetre of draft mark translates to approximately 50 tons cargo for an average bulk carrier. This extra throughput can have significant flow-on economic benefits beyond the ship operator. However the ports needs to plan loading and sailing schedules and cargo capacity around these environmental restrictions.

A typical bulk export operation sets a vessel's cargo loading targets around 24 hours prior to sailing time, which is typically aligned with high tide. This is long enough for environmental conditions to change and observed water levels to deviate significantly from tide tables. Port operations rely on forecasts to plan and monitor these changes to ensure the appropriate loading of cargo to their vessels. The plan needs to account for maintaining safe under keel clearance (UKC) of their vessels during the transit from berth to deep water. Any adverse changes in water level predictions may result in sailing delays or cancelation, or even become a safety hazard.

2 CHALLENGES IN PORT OPERATIONS

Determining the maximum safe sailing draft of a vessel requires the accurate estimation of UKC for the planned sailing. Estimation of UKC is a multi-factored problem; variables include vessel characteristics (particulars and planned loading state, including draft), transit characteristics (e.g. channel depth the planned speed) and environmental conditions predicted for the time of sailing (wave, tides, and currents). To take these dynamic forcings into account, many Australasian ports use Dynamic UKC® (DUKC®) as a decision support system to predict UKC and safe draft and sailing time combinations. Tide and tidal anomaly forecasts intrinsically affect UKC, hence accurate water level predictions (tide plus anomaly) are a direct factor in the safe navigation of these depth-constrained waterways. Additionally, by reducing the uncertainty of water level forecasts, loading drafts can be proportionally increased, yielding significant economic benefits.

2.1 'TIDES' AND SEA LEVEL

Variations in coastal water levels are generically referred to as 'tides'. For the purposes forecasting these tides, useful distinctions can be made between sea level signals attributed to distinct oceanographic phenomena. The near ubiquitous decomposition of sea level of this nature is between the official harmonic tide predictions and the 'tidal residual' or anomaly.

2.1.1 HARMONIC PREDICTIONS AND TIDE TABLES

Tide tables are based on the harmonic analysis of long records of observed sea level. In Australia, the official National Tide Tables promulgated by the Australian Hydrographic

Service are primarily calculated by the Bureau of Meteorology Tidal Unit [1] using harmonic methods.

As a sea level forecasting approach, standard harmonic methods are remarkably successful and robust. Tide table predictions can be produced years in advance and are fundamental to planning of port operations.

Harmonic tide methods exploit the fact that at most coastal locations sea level variations are dominated by phenomena highly correlated with the relative motion of the Earth, Moon, Sun and other astronomical bodies. This correlation reflects the significant role of gravitationally forced basin-scale long-waves shoaling onto continental shelves. It is notable however, that the relationship between observed sea level and tidal gravitation is complex and localised. Furthermore, not all of the signal regularly occurring at tidal frequencies, and usefully included in tide tables, are due to astronomical effects.

Tide tables are stated to be valid for 'average meteorological conditions' [2] and storms are often a driver of relatively short-lived sea level deviations. Storm impact need not be localised and shelf-scale phenomena can propagate deviations for many thousands of kilometres – notably along Australia's southern shelves [3].

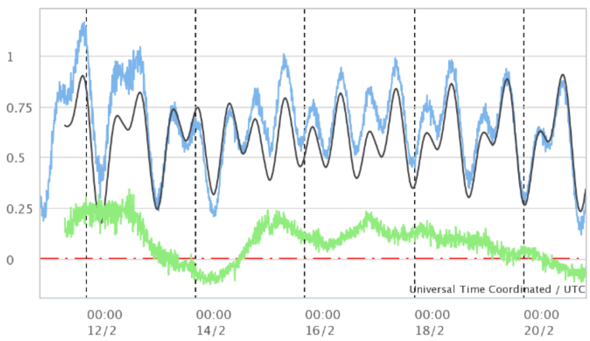

Figure 1. Example of difference between observed sea level and official tide predictions in Southern Australia. Tide table predictions (black) are a good estimate of observed water level (blue), but the anomaly or 'residual' (green) can be a significant consider

Figure 1 so that the deviation is apparent to pilots and operators. User-focussed statistical approaches can be used to account for the deviation [4], but ideally the water level anomaly should be foreseen and factored into the sailing plans.

Towards predicting water level anomaly, the heterogeneous phenomena that force the deviations need to also be predicted and understood; no trivial task. In this study we were fortunate to work with two sophisticated forecasting models operating at distinct spatial scales and offering distinct prognostic information.

2.2 OPERATIONAL WATER LEVEL FORECASTS

Numerical fluid dynamic models of ocean circulation have become increasingly viable for operational use in recent decades, largely due to the combined advances in computational capacity and real-time oceanographic observations.

Global ocean 'weather' phenomena such as mesoscale eddies, seasonal mass distribution, coastal currents and shelf waves are represented by the Australian Bureau of Meteorology's OceanMAPS system. Daily forecasts of the global ocean state for 7-day lead times are produced operationally; exploiting satellite observations and data assimilation techniques in a manner analogous to global weather forecasting systems [5] [6].

From this foundational capacity, a coastal sea level forecasting service has been developed that aggregates the sea level anomaly forecasts with standard tides, barometric pressure and other data to enable direct comparison to real-time tide gauge observations [7].

At the finer localised spatial scale, Met Ocean Solutions (MSL) have solved a limited area sea level model for the Port of Geelong. Their nested Regional Ocean Modelling System (ROMS) computes atmospheric forcing for the South Australian continental shelf [8]. A 5 km resolution parent nest covering most of the south coast of Australia provides shelf scale residual water levels for a local 300 m Port Phillip Bay nest (Figure 2). The importance of the rather large parent nest lies in considering the remote effects of coastal trapped wave propagation from west to east triggered by low pressure systems propagating along the coast, which has proven to greatly improve the residual elevations accuracy. The atmospheric forcing consists of winds and mean sea level pressure derived from a customised MSL 9 km WRF model.

These two modelling systems target quite distinct representations of oceanographic phenomena, and may offer somewhat complimentary prediction insight. The challenge in forecasting is optimising the skillset of multiple numerical models in one combined prediction.

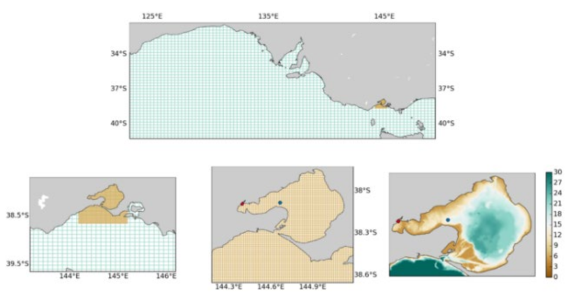

Figure 2. Spatial representation of the current ROMS model representing Victoria and Port of Geelong. The mid and right two lower panels show the high resolution of the model.

2.2.1 SEA LEVEL FORECASTS FROM THE OCEANMAPS GLOBAL MODEL

OceanMAPS provides a generalised best-estimate of the 3D physical state of the global ocean state with a primarily blue-water target (aimed primarily at forecasting ocean circulation away from the coast), from which sea level anomaly can be output. The spatial representation of the Australian coastline is discretised at ~10km and intentionally excludes embayments such as Port Phillip in Victoria as indicated by Figure 3.

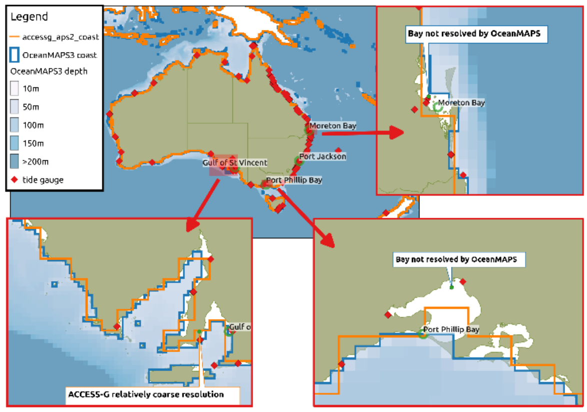

Figure 3. Spatial representation of the coast by current version of OceanMAPS. Blue lines with fine steps show coastline in the ocean model grid; orange lines at coarse steps indicate equivalent coastline within the atmospheric forcing model. Note that some embayments are intentionally excluded from the model.

Regardless, the system provides skilful prognosis of sea level anomalies *within* the Bay at synoptic time scales. This reflects the significance of sea level variations at the open ocean entrance to the Bay. This skill is quantified against observed water levels at St Kilda by two distinct measures in Figure 4 and Figure 5.

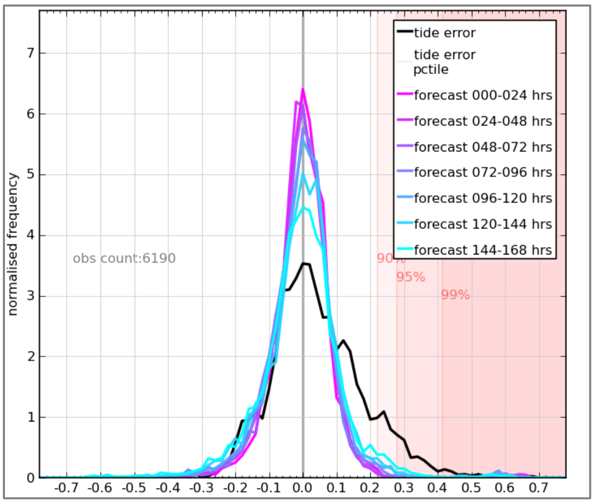

Figure 4. Normalised error distributions for 1-hourly sea level at St Kilda, Victoria. Conventional tidal residual distribution (black) is relatively broad with notable tail at upper end. Forecast errors for the OceanMAPS-based aggregated sea level shows a much narrower distribution. As expected for skilful numerical forecasts, the peakedness of distribution decreases with forecast lead time.

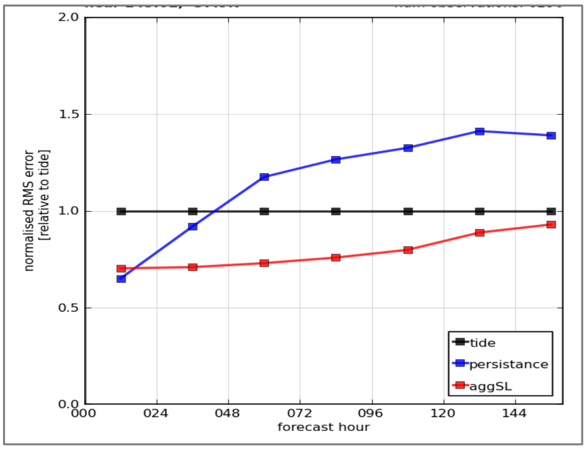

Figure 5. RMS error growth in daily bins for OceanMAPS-based aggregate sea level forecasts (red) is better relative to conventional tidal residuals (black). Comparison with forecasts based on persistence of observed residual at forecast base time (blue) show notable cross-over points. Persistence on average out-performs within the first day, but rapidly decays in value.

2.2.2 SEA LEVEL FORECASTS FROM ROMS MODEL

The MSL storm surge forecast model has demonstrated good skill in representing the residual water levels at Geelong. Table 1 and Figure 6 show the results of the model validation against measurements. Results accuracy does not seem to degrade significantly ahead of cycle initialization times. In fact, there seems to be a trend of decreasing bias going forward in the forecast horizon, which could be related to slight dissipation trends either in the wind forcing or the hydrodynamic model itself. However, those trends are negligible compared to the overall bias.

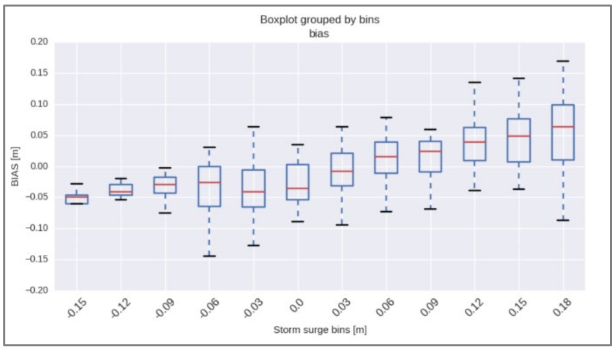

Figure 6. Box and whisker plots presenting the MSL model BIAS statistics along specific storm surge 3 cm bins considering the 29 analyzed forecast cycles.

The model results are more consistent for negative surges (lower water levels), and the negative BIAS noted on these particular events means the predictions are on the conservative side, which is a good outcome for under keel clearance purposes. There are relatively more model fluctuations on the positive (higher water levels) surges. Although the data population is limited to the number of forecast cycles (29) analyzed, Figure 6 offers a good indication of the degree of confidence that can be expected for different magnitudes of the storm surge.

Table 1. Summary statistics for MSL nowcast/forecast and measurements comparison at Pt. Richards. MAE stands for mean absolute error and RMSE stands for root mean square error. Units in [m]. The "T+?h" refers to combined forecast cycles time series starting from a time (in hours) ahead of the cycle initialization.

	NowCast	T+24 h	T+28 h	T+72 h	T+96 h	Ave.
BIAS	0.013	0.009	0.01	0.009	0.005	0.009
MAE	0.049	0.045	0.045	0.046	0.044	0.055
RMSE	0.065	0.055	0.056	0.058	0.054	0.058

2.3 MAINTENANCE

The dependence of operational decision support systems such as the DUKC® on third-party service providers raises issues when employing local statistical downscaling methods to match model forecasts with observation sites. Notably, routine upgrades to numerical models such as OceanMAPS or ROMS can introduce unexpected changes to the forecast's characteristics (in relation to observations). This can cause the predictions used in the estimation of Dynamic UKC® to change, sometimes with deleterious impact on operations.

To manage the impact of these routine upgrades, providers will usually allow a period of overlap to allow the forecast characteristics to be evaluated and changes to be made as required. A statistical persistence-based forecast model is also incorporated into the system as a ground-truth and back-up model.

3 ADAPTIVE FORECAST SKILL EVALUATION & ASSIMILATION

In order to operationally handle model changes in forecast model characteristics more gracefully and with less impact on users, these changes should be automatically detected and the statistical model should adapt in a short time frame.

A stochastic approach is used to construct an adaptive model, where the forecasts are characterised as probability distributions, and retrospectively compared to the distribution of the target observations. The stochastic approach means that the prediction can be solved statistically, but not deterministically.

The new approach consists of two parts: an adaptive forecast skill evaluation to provide the basis for statistical assimilation, and recursive Bayesian estimation (BRE) to dynamically combine (assimilate) the forecasts. The BRE model compares the most recent assimilated prediction with new information from the forecast models [9] [10]. This creates a feedback loop, so that the model output is no longer a deterministic product of the measured and forecast data inputs. This method is applied to a statistical persistence as well as any available externally generated numerical forecasts, such as those from OceanMAPS and ROMS.

Tidal residuals are modelled with a normal Gaussian distribution. Implicitly, this also assumes that the forecasts are normally distributed. With this assumption allowed, Student's t-distribution can be used to increase the "uncertainty" based on sample size, which is particularly helpful when only a small numbers of forecast packets are available. The forecasts are thus weighted less strongly than a direct evaluation would imply. Similarly, by limiting the number of packets that are evaluated to the most recent (e.g. two months), the model responds to the skill of the forecasts adaptively so that if the model changes are incorporated accordingly [11] [12] [13].

4 RESULTS

This study tested the robustness of the adaptive model for two months period. The test covers observations, astronomical tide and numerical forecast for the test period from for 2016-Oct-01 until 2016-Dec-02. This period observed 116 potential high water sailing opportunities.

Figure 7 shows an example BRE application to numerical forecasts. The maroon and dashed green lines represent the forecasts from Bureau of Meteorology (OceanMAPS) and MSL (ROMS) for 14 Oct, 2016, respectively. In Figure 7both numerical forecasts under-predict the observed residuals. BRE successfully detected and had elevated the transformed forecasts in the lower figure.

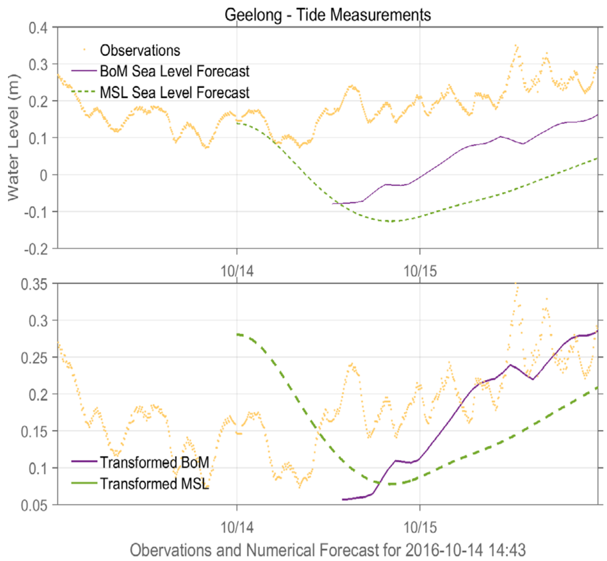

Figure 7 shows an example time series of numerical forecast for 14 Oct 2016 and shows the updated BRE transformed forecasts from the Bureau of Meteorology and MSL. Note that the transformed forecasts are stochastic and illustrated as a range.

The BRE transformed 64 Bureau of Meteorology packets and 56 MSL packets to be combined with the statistical predictions. For every new observation, a persistence based forecast is also produced. This persistence prediction is then assimilated with the numerical forecasts. Figure 8 shows an example assimilated prediction produced for 14 October, 2016. The green shaded area shows the 1-sigma confidence interval.

The assimilated water level predictions for Geelong are assessed using forecast horizon evolution. This approach assesses the potential impact of variations in water level predictions for the vessel's scheduled transit as the time of sailing approaches. In this analysis, persistence predictions are used as a control case.

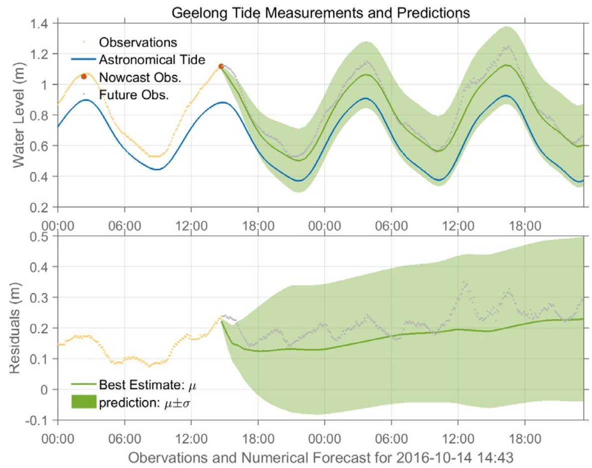

Figure 8 shows an example assimilated prediction produced for 14 October, 2016.

Numerical forecasts considerably improve on the persistence prediction in Figure 9. The figure is a result of hourly issued conservative water level predictions for 116 different sailing times. Each prediction was aimed to be the best estimate. The assimilated forecast distribution is a lot tighter compared to the persistence one, thus the assimilation reduces the uncertainty in the predictions.

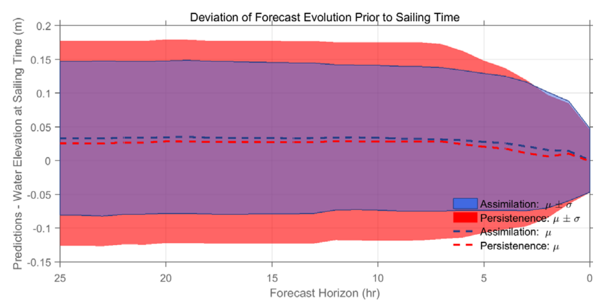

Figure 9 compares BRE assimilated forecast against a persistence based model. Assimilation predictions include both the BoM and MSL numerical forecasts. Analysis consists of 116 Sails between 2016-Oct-01 and 2016-Dec-02.

In Figure 10, the range of prediction error as a function of forecast horizon is shown as shaded areas to compare the benefit of assimilating both the BoM and MSL forecasts (blue), as opposed to only having BoM forecasts (yellow) or only MSL (red). While the MSL forecasts introduce some positive bias, the complementary skill of the two forecasts reduce the range of uncertainty overall. When producing stochastic forecasts, the reduction in uncertainty is especially useful when producing conservatively biased estimates which are preferable for use in the DUKC® decision support system.

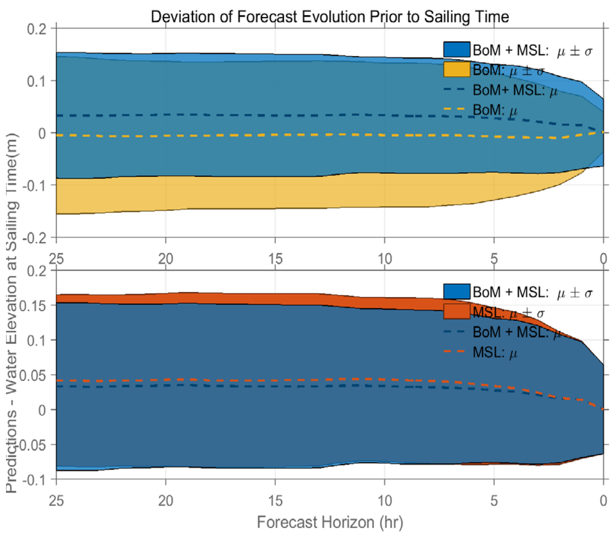

Figure 10 shows forecast range and standard deviation from conservative predictions. The combined assimilation is compared against prediction that are assimilated with the Bureau of Meteorology and MSL forecasts only. Analysis consist of 116 Sails between 2016-Oct-01 and 2016-Dec-02.

Ideally combining multiple numerical forecasts that provide additional information should improve the overall prediction, and indeed this is shown in(Figure 10). The primary result is that the stochastic uncertainty is reduced with the two forecasts combined (with persistence) compared to either one alone.

5 CONCLUSION

This investigation concluded that a Bayesian recursive approach can evaluate and assimilate multiple forecasts of tidal residuals adaptively. The preliminary model successfully adapted seasonal changes in tidal residuals and improved water level predictions for operational use.

The proof-of-concept model in this study successfully assimilates water level predictions with the aid of two numerical forecasts. This adaptive approach should prove to be invaluable for operational use. The approach successfully combined MSL's Geelong and the Bureau of Meteorology's Port Phillip Bay sea level anomaly forecasts.

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