Ocean Modelling 100 (2016) 20–30

Contents lists available at ScienceDirect

Ocean Modelling

journal homepage: www.elsevier.com/locate/ocemod

Downscaling and extrapolating dynamic seasonal marine forecasts for coastal ocean users

Jarno Vanhatalo[a,*], Alistair J. Hobday[b], L. Richard Little[b], Claire M. Spillman[c]

[a] Department of Environmental Sciences, University of Helsinki, P.O. Box 65, FI-00014 University of Helsinki, Finland
[b] CSIRO Oceans and Atmosphere, Castray Esplanade, Hobart, Tasmania 7000, Australia
[c] Bureau of Meteorology, GPO Box 1289, Melbourne, Victoria 3001, Australia

ARTICLE INFO

Article history:
Received 31 December 2014
Revised 2 December 2015
Accepted 2 January 2016
Available online 29 January 2016

Keywords:
POAMA
Seasonal forecast
Statistical downscaling
Coastal extrapolation
Great Australian Bight
Gaussian process

ABSTRACT

Marine weather and climate forecasts are essential in planning strategies and activities on a range of temporal and spatial scales. However, seasonal dynamical forecast models, that provide forecasts in monthly scale, often have low offshore resolution and limited information for inshore coastal areas. Hence, there is increasing demand for methods capable of fine scale seasonal forecasts covering coastal waters. Here, we have developed a method to combine observational data with dynamical forecasts from POAMA (Predictive Ocean Atmosphere Model for Australia; Australian Bureau of Meteorology) in order to produce seasonal downscaled, corrected forecasts, extrapolated to include inshore regions that POAMA does not cover. We demonstrate the method in forecasting the monthly sea surface temperature anomalies in the Great Australian Bight (GAB) region. The resolution of POAMA in the GAB is approximately $2^\circ \times 1^\circ$ (lon. × lat.) and the resolution of our downscaled forecast is approximately $1^\circ \times 0.25^\circ$. We use data and model hindcasts for the period 1994–2010 for forecast validation. The predictive performance of our statistical downscaling model improves on the original POAMA forecast. Additionally, this statistical downscaling model extrapolates forecasts to coastal regions not covered by POAMA and its forecasts are probabilistic which allows straightforward assessment of uncertainty in downscaling and prediction. A range of marine users will benefit from access to downscaled and nearshore forecasts at seasonal timescales.

1. Introduction

A wide range of managers and users of the marine estate require access to weather and climate information, such as wind, waves and ocean temperature, in order to plan strategies and activities on a range of temporal and spatial scales (Eveson et al., 2015; Hobday et al., 2016). Fishers consult online maps to plan fishing locations, surfers look to wave buoy measurements for ocean swell information, and sailors check marine weather forecasts. Other resource-based needs are also apparent; fishery and aquaculture managers often seek information on impending conditions that threaten production (Spillman and Hobday, 2014; Eveson et al., 2015) or to regulate access to marine areas (Hobday and Hartmann, 2006; Howell et al., 2008; Hobday et al., 2011). Hence, information on future conditions is highly valuable. Coastal marine forecast capability has increased in recent years, in part due to advances in remotely sensed data quantity and quality as well as improvements in ocean modeling. For example, high resolution regional forecast models can now forecast few days ahead[1]. Satellite-based data can be very high resolution though is generally limited to surface properties and also does not indicate future conditions. Conversely, seasonal process-based models that provide forecasts over weeks to months, often have lower offshore resolution and limited information for inshore coastal areas (Hobday and Lough, 2011; Stock et al., 2011). Global ocean models simulate a range of ocean processes and thus generate information at a range of time scales on surface and sub-surface temperatures, vertical structure, salinity, currents, and even productivity (Oke et al., 2008; Stock et al., 2011; Matear et al., 2013). Progress has been made in developing methods to dynamically or statistically downscale global model information to a finer scale (e.g. Oke et al., 2008; Oliver and Holbrook, 2014; Chamberlain et al., 2012), though relatively coarse resolution is typical due to computational limitations (Stock et al., 2011). Among coastal users in particular, there is need for seasonal forecasts at even finer resolutions that reflect local environmental heterogeneity (Stock et al., 2011; Spillman and Hobday, 2014).

* Corresponding author. Tel. 358 44 3765458.
E-mail address: jarno.vanhatalo@helsinki.fi (J. Vanhatalo).

[1] see e.g., http://www.bom.gov.au/oceanography/forecasts/.

http://dx.doi.org/10.1016/j.ocemod.2016.01.004
1463-5003/

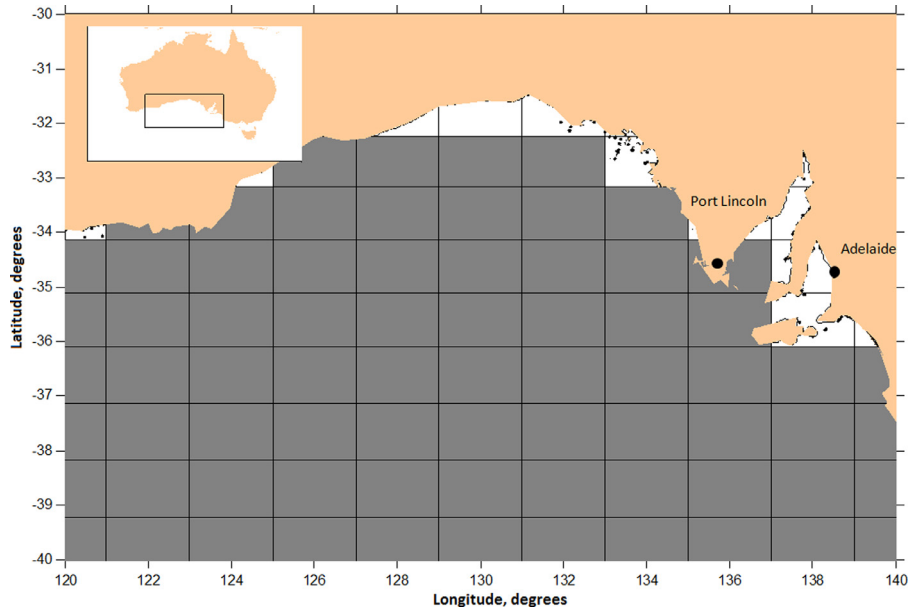

Fig. 1. Map of the Great Australian Bight study domain, overlaid with the POAMA (Model 1) grid (gray). Coastal areas not covered by POAMA are shown as white grid cells.

Ocean forecasts can be near-realtime (e.g. Brassington et al., 2007, 2012), seasonal (Spillman, 2011; Hudson et al., 2013) or climate scale (e.g. Taylor et al., 2012). Recently, dynamical seasonal forecasts based on the Australian Bureau of Meteorology's Predictive Ocean Atmosphere Model for Australia (POAMA) have been used for management of a range of activities including land-based prawn aquaculture (Spillman et al., 2015), coastal cage aquaculture of salmon (Spillman and Hobday, 2014), offshore tuna fisheries (Hobday et al., 2011), and coral reef management (Spillman, 2011; Spillman et al., 2012). Several of these applications have successfully used downscaled forecasts because the environmental variables of interest are correlated across space (e.g. Spillman et al., 2015), but these approaches are of limited value in areas where the variables are not correlated, or not simulated by POAMA such as nearshore coastal areas.

Fine scale seasonal forecasts covering coastal waters so far have been elusive, even though there is increasing demand for them to support decision making at present (Hobday et al., 2016), and in a changing climate (Hobday et al., 2014). Generation of fine scale information (<10 km) from ocean models like POAMA is possible with statistical downscaling techniques (e.g. Fuentes and Raftery, 2005, Berrocal et al., 2008) commonly applied in weather forecasting (Kleiber et al., 2011). However, extrapolation to nearshore areas is also required; thus a method to allow both downscaling and spatial extrapolation to coastal areas is highly desirable.

Recently statistical analyses have been applied to a wide range of deterministic weather and seasonal forecasts to produce downscaled, bias-corrected predictions (e.g. Fuentes and Raftery, 2005; Kleiber et al., 2011; Salazar et al., 2011, Vanhatalo et al., 2013b) by representing model variables as a Gaussian process (GP) and treating the process model and observational data as complementary sources of information (Salazar et al., 2011). The benefits of this approach are that the different scales of the model and the observations, as well as model uncertainty, can be explicitly incorporated. Here, we advance from these approaches and demonstrate a new technique that combines data from a coarse-scale process model (POAMA) with a fine scale observational correction to produce fine scale forecasts, useful up to four months in advance, and extending to coastal areas not covered by POAMA. Specifically, we use GPs, to i) correct possible biases in the POAMA SST forecast, ii) statistically downscale the POAMA forecast, and iii) extrapolate the new forecast into the coast where the raw POAMA forecasts do not reach (e.g. Fig. 1). Moreover, our statistical approach is probabilistic which allows straightforward assessment of uncertainty in the downscaling, and provides a tool for supporting risk and decision analysis (Little et al., 2015).

We illustrate our approach using sea surface temperature (SST) and its anomalies (SSTA) in the Great Australian Bight (GAB; Fig. 1), a region that is home to a wide range of valuable marine industries influenced by ocean temperatures including a southern bluefin tuna fishery and oyster aquaculture (ABARES, 2013; Eveson et al., 2015). The technique, however, will have a wide range of applications in other regions, including inshore aquaculture industries, coral reef management and sea level warning systems.

2. Materials and methods

2.1. Observational data

We focus on monthly SSTA (the average monthly deviation from the long term monthly mean field) from model hindcasts (retrospective forecast) and observations for the period 1994–2010. Historical satellite SST data from the NOAA Pathfinder satellites, archived and composited at a weekly resolution of approximately 9×9 km (Hartog and Hobday, 2011), were used for both model training and forecast validation over the period 1994–2010. The data were averaged by month and aggregated into a lattice grid of size 1° in longitude and 0.25° in latitude, which is sufficient in this study for proof of concept.

2.2. Forecast model suite

Our new method hybridizes fine-scale observational data (NOAA satellite data) and coarse-scale dynamical model output (POAMA) to generate fine scale model forecasts, extended to coastal areas not covered by POAMA (Fig. 1). The process combines POAMA predictions and satellite observations of SSTA in a statistical downscaling model. This is shown conceptually in Fig. 2. For this reason, we compare it with both pure POAMA and pure statistical model output. All the models are summarized in Table 1 and introduced below.