

# Coupled Atmosphere–Ocean Modelling

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*The concept of “coupled modelling” is a broad one with many different meanings and understandings within the operational oceanography community and beyond. Here we focus specifically on coupled atmosphere-ocean models and how these are developing for different timescale prediction systems. After a general introduction, we briefly describe the status of coupled modelling on climate timescales (the most mature area), followed by seasonal and decadal timescales. We then consider short- and medium-range coupled timescales which are the least mature, but the area of most relevance to the future of operational oceanography (and numerical weather prediction). The third section describes new frontier applications of these systems on the different timescales. Finally, we provide some concluding remarks on coupled modelling in the fourth section.*

## Introduction to Coupled Modelling and the Main Challenges

The chapter is predominantly about prediction systems making use of a coupled atmosphere-ocean model. By this we would most commonly be referring to a numerical model of the atmosphere, usually with an associated land-surface model, which is 'two-way coupled' (at least daily, if not more frequently e.g. hourly) to a numerical model of the ocean, often with an associated sea-ice model. The exchange of coupling fields – variables like sea surface temperature and currents from ocean to atmosphere, and heat and momentum fluxes from atmosphere to ocean – is often accomplished by the use of a separate coupling code (like OASIS-MCT, Craig et al., 2017) or framework (like ESMF, DeLuca et al., 2012) providing a flexible way of linking component models and controlling the exchange and interpolation of coupling fields. Other systems use bespoke in-house coupling code or libraries in order to more “tightly” couple the component models. This can allow more control over when and how the models are run. Still other systems, where frequent coupling is not considered to be so essential, may write the required coupling fields as diagnostics to a file which is then used as input by another model; in the most extreme this is what might be referred to as “one-way coupling” although there is an unclear boundary between this and what would usually be considered as having separate models using each other's boundary conditions or “forcing”. Many coupled models of the earth system include other physical or biogeochemical components which we mention where relevant (note that ocean-wave coupling is covered in Chapter 14 by Arduin and Orfila).

The advantage of genuinely coupled models is that changes in one model (e.g., evolution of sea surface temperatures in the ocean model in response to the atmospheric state) can directly and

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immediately influence the other model (e.g., modified heat and moisture fluxes into the atmospheric boundary layer and beyond). In ocean-only models, the absence of any feedback on the atmospheric forcing variables, e.g. winds, temperature and humidity, can cause many inaccuracies (see e.g. Griffies et al., 2009). This is true particularly if the forcing used is obtained from an atmosphere model which originally “saw” a significantly different ocean surface boundary condition; differences in areas of ice cover are especially problematic in this regard because heat and moisture fluxes over the open ocean are very different from those over sea ice.

A number of recent studies (see e.g. Renault et al., 2016) have focussed on the effect of including ocean currents in the calculation of the atmosphere–ocean momentum exchange. Although this can be included in forced ocean systems it will tend to lead to an over-damping of the eddy field if there is no attempt to parameterise the effect of the current feedback on the atmospheric winds. It should be noted that even in a coupled system there can be related subtleties regarding the exact definition of the observational wind fields which may have been assimilated in the atmospheric component (see discussion in Chapter 10 by Bourassa regarding wind stress).

In practice, on shorter timescales it may be possible to achieve some, or even the majority, of these feedbacks by something short of full “two-way coupling”. However, this doesn't necessarily reduce the complexity of the system and in some cases can simply hide problems, like model drifts or incorrect fluxes, which a more fully coupled system is forced to confront.

There is much still to understand regarding air–sea coupling, particularly at short spatial and temporal scales. The impact of different choices regarding the “sequencing” of model components, (e.g., running models concurrently or sequentially, the use of averaged or instantaneous fields if not coupling every time-step) are often ignored but will have impacts for stability, conservation and accuracy. Some of the numerical issues relating to ocean–atmosphere coupling are discussed in Lemarié et al. (2015) which also demonstrates the potential of iterative methods to provide more exact solutions to overcome the problems of asynchronous coupling. There are specific numerical complexities regarding the coupling of sea ice to both atmosphere and ocean – see for example Beljaars et al. (2017) and also West et al. (2016) regarding the impact of different choices for the location of the thermodynamic atmosphere–ice interface in fully coupled models.

From what has been discussed so far, it is already becoming clear that one of the big challenges of coupled modelling is the associated complexity, and the need to link together different component models in a way which is flexible, but also scientifically sensible and computationally affordable. Additional complications arise because these models often use different horizontal grids, are developed by different communities and have different priorities, timescales and governance for their development. Decisions on the exact coupling approach will be driven by a whole variety of factors including the technical and computational infrastructure available, and the remit of a particular institution – this will affect the model outputs of most interest or relevance from each system.

Similar considerations will also affect choices about the horizontal and vertical resolution of different model components – for example, whether an ocean model in a coupled system needs to

be eddy resolving, or even whether some kind of mixed layer ocean is sufficient in cases when the primary concern is feedbacks on the atmosphere over short timescales.

Many operational and research centres are now pursuing a “seamless” approach (Hurrell et al., 2009; Brown et al., 2012) whereby model configurations are kept as consistent as possible, except in some cases for resolution, across a range of applications and timescales. This attempts to exploit model development efficiencies, reduce technical overheads, and facilitate increased understanding of model errors which are common across timescales. However, there are inevitably compromises due to the different requirements for different applications. For example, energy conservation and avoidance of numerical diapycnal mixing are both much more important on climate timescales.

Initialization is one of the other main challenges of coupled prediction. On longer timescales this is a particular issue for the ocean components, whereas on shorter timescales the consistent initialization of both atmosphere and ocean (and sea ice) becomes increasingly important. This is necessary to avoid spurious initialization “shocks” or adjustments (Mulholland et al., 2015) which degrade the forecast quality over the first few days. These challenges will be discussed further in the relevant sections below (the specific area of initialization using coupled data assimilation is more fully covered in Chapter 17 by Hoteit et al.).

## Coupled Modelling for Different Timescales

This chapter does not attempt to provide anything close to a comprehensive history and review of coupled forecasting on these various timescales, but instead tries to highlight some of the aspects of these systems which relate most closely to the ocean, and also to emphasise the new frontiers in these areas of coupled modelling.

### Climate (10 to 100+ years)

Coupled atmosphere–ocean models have been used for climate modelling since the 1960s due to the ocean’s fundamental role in the global heat budget. At first these models usually required a form of “flux adjustment” in order to adequately simulate present-day climate. This was clearly undesirable and cast serious doubt on the ability of these models to make reliable projections about future climate. Ocean model improvements, including the use of the spatially varying Gent–McWilliams parameterization (Gent and McWilliams, 1990) to adiabatically release potential energy, were thought to be significant in allowing the removal of flux adjustment in the 1990s (Gordon et al., 2000). Climate models have included many new interactively coupled components over the last half century including land–surface and sea–ice models, and an increasing number of other “earth system” components as described below.

As on other timescales there is continued debate about “resolution versus complexity”. Can we have confidence in climate projections from modelling systems which have a poor present-day climate mean state, or which fail to adequately simulate aspects of the present-day climate system like storm tracks, the hydrological cycle, clouds, and large-scale ocean circulation? On the other hand, can we have confidence in climate projections from models which fail to include aspects of

the earth system, most notably the carbon cycle, which may become increasingly important in future? These questions motivate two of the new frontiers of climate modelling.

Firstly, there is an increasing drive to perform climate model simulations with both atmosphere and ocean resolutions comparable to, or in some cases even exceeding, those used for operational numerical weather prediction and operational ocean modelling systems. Some examples include Community Climate System Model (CCSM, Gent et al., 2011), GFDL Climate Model 2 (Delworth et al., 2006) and MIROC5 simulations using  $1/10^\circ$  ocean configurations; and both HadGEM3 (Hewitt et al., 2011) and EC-Earth (Hazeleger et al., 2010) simulations using a  $1/12^\circ$  NEMO ocean configuration. The HiresMIP initiative (Haarsma et al., 2016) and associated activities like the European Union Horizon2020 PRIMAVERA project (PRIMAVERA, 2018) are helping to drive understanding of these very high resolution models through an inter-comparison of simulations from a number of different modelling centres. These models generally show an improved present-day climate mean state compared to their lower resolution counterparts (Griffies et al., 2015; Hewitt et al., 2016) in regions including the North Atlantic and Southern Ocean. We note, however, that care should be taken when interpreting relatively short climate runs which may have been “tuned” to have an appropriate radiation balance at a particular resolution, or may still be drifting over time. Some of the improvements between eddy-resolving (e.g.,  $1/12^\circ$  resolution) and eddy-permitting (e.g.,  $1/4^\circ$ ) ocean models may be indicative of poor parameterization choices at the lower resolutions; however, it is increasingly argued that  $\sim 1^\circ$  resolution models are not appropriate even for climate studies (Bryan et al., 2010; Kirtman et al., 2012; Roberts et al., 2016). Despite running without data assimilation, high-resolution climate models can provide a useful source of information to help improve initialized coupled model predictions on shorter timescales. This includes analysis of how correlations between the sea surface temperature and the atmospheric boundary layer, and above, compare with those derived from observational products (see e.g. Bryan et al., 2010; Chelton et al., 2010; Roberts et al., 2016; Parfitt et al., 2016; Parfitt et al., 2017; many of these studies are also reviewed in Hewitt et al., 2017). Although both atmosphere and ocean components of these models are far from perfect (for example, see Chapter 2 by Fox-Kemper on the lack of a resolved sub-mesoscale) in many regards their performance does appear to be converging towards a representation of processes which is in better agreement with observations. Long, free-running high-resolution climate models can therefore inform the development of coupled models on shorter timescales, and provide confidence that these models are able to simulate features at scales the data assimilation will be trying to correct in an operational system. To some extent biases in such models can also be linked with biases on shorter timescales. However, this has to be done carefully and with a good deal of understanding of the underlying processes (see e.g. Hermanson et al., 2017).

The second significant “new frontier” of climate models is the move towards earth system models of increasing complexity, and with a whole variety of different physical and biogeochemical model components. “Earth system” is defined in various ways, but one meaning is that such models include a full representation of the carbon cycle. This allows any response of the carbon cycle to either increased carbon dioxide emissions, or a warmer climate, to be represented. The individual

terms in the global carbon cycle are so large that even small changes could have a significant impact on the amount of emitted carbon dioxide which remains in the atmosphere, and therefore on the amount of future warming. In the UK, the “UKESM1” model being prepared for CMIP6 (Eyring et al., 2016) will include full atmospheric chemistry and aerosols, terrestrial carbon cycle and vegetation, marine biogeochemistry, and dynamic ice sheets, as well as “traditional” physical model components. To achieve this in a global model which can be used for century long integrations inevitably requires compromises on resolution; despite the known deficiencies a  $1^\circ$  ocean model will be used for most of the simulations. Both the atmospheric chemistry and ocean biogeochemistry in this model will run on a coarsened grid, and in the coming years there will most likely be further effort to ensure that the resolution in such models is only placed where it is genuinely required. This may include adoption of unstructured mesh or adaptive mesh refinement techniques (e.g., using the AGRIF package described in Debreu et al., 2008), or more sophisticated hybrid vertical coordinates (see Chapter 12 by LeSommer et al.) rather than the more traditional model grids and z-level coordinates still used for the ocean component in the majority of climate models.

Climate projections are not considered to be an “initial value problem” but that is not to say that initialization is unimportant. Projections of future climate will usually be started from a close-to-equilibrium “spun-up” initial state representative of pre-industrial (or present-day) climate forcing; this ensures that any future climate change signal is not too contaminated by model drifts. The challenge to reach such a state, which is not too far from the observed climate, remains a significant one. It is closely related to the common practice of “tuning” climate models – for example, modifying the aerosol climatology, or adjusting parameters in the cloud scheme or ocean vertical mixing scheme – to achieve a realistic net radiative balance and ocean temperature structure.

The initialization challenge becomes greater at both of the new frontiers described above. In both cases the models are very expensive to run, and additional components – particularly those poorly observed historically, or with inherently longer timescales like ice shelves – may take longer to reach a spun-up equilibrium state. The ocean carbon cycle in Earth system models will often require a spin-up of several thousand years. This would be too long to perform in a fully coupled framework and so strategies have to be devised to, for example, use a combination of coupled runs, and forced runs using atmospheric variables from those coupled simulations. This allows a suitable equilibrium state to be obtained although there is no guarantee it is representative of an actual observed realisation, particularly in a non-stationary climate.

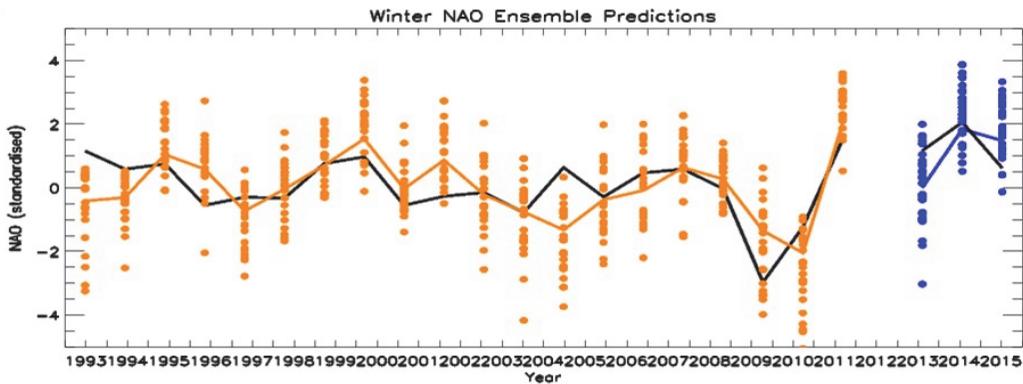
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### Seasonal (3-12 months) and decadal (1-20 years)

Statistical methods have been used for seasonal forecasting for many decades, and continue to be used in combination with the dynamical coupled atmosphere-ocean models which are now also utilised. On these timescales, the atmospheric initial conditions become less important. Instead the low frequency forcing from the ocean (e.g., sea surface temperature patterns related to the El Niño Southern Oscillation, or ENSO - see Chapter 23 by McPhaden), and aspects of the land surface and sea ice, begin to provide the dominant contributions to predictability. Although the majority of this predictability originates in the tropics, the “teleconnections” to impacts elsewhere have been well

known for many years. As well as direct circulation changes, Rossby wave trains can propagate from the tropics to mid and high latitudes influencing e.g. weather patterns over North America and the North Atlantic Oscillation.

Dynamical seasonal forecast models require good ocean sub-surface observational coverage for initialization – this was significantly improved with the development of the TAO/TRITON (Tropical Atmosphere Ocean/Triangle Trans-Ocean Buoy Network) moored buoy array in the 1980s. Models also need to have a good representation of ENSO variability (still problematic in some regards but improved with higher horizontal resolution in both atmosphere and ocean components; Shaffrey et al., 2010), and a good representation of the mechanisms by which the tropical predictability “leaks” to higher latitudes, as well as a correct model response to these influences. As a result of uncertainty in both initial conditions and model parameterisations, seasonal (and decadal) forecasting systems make use of ensembles of model simulations to provide probabilistic forecast information. These ensembles are generated using perturbed initial conditions and sometimes also stochastic physics.



**Figure 16.1.** Predictability of the winter North Atlantic Oscillation, measured as the sea level pressure difference between Iceland and the Azores. The NAO in observations (black line), ensemble mean GloSea5 forecasts (orange line), and individual ensemble members (orange dots) in winter (December to February) hindcasts are shown, normalized by their respective standard deviations. Anomalies are for December to February, and forecasts were initialized from dates centred on 1 November. The correlation score of 0.62 is significant at the 99% level according to a t test and allowing for the small lagged autocorrelation in forecasts and observations. Updated from Scaife et al. (2014) with real-time forecasts (blue line and dots).

One of the notable advances in seasonal forecasting over the last few years has been the improvement in the ability to forecast the North Atlantic Oscillation (NAO). The seasonal forecast system at the UK Met Office (GloSea5) demonstrated an anomaly correlation of around 0.6 (see Fig. 16.1) for predictions of winter NAO from forecasts initialized in November (Scaife et al., 2014); similar results have subsequently been obtained in other systems (e.g., Weisheimer et al., 2017). Sources of this predictability include ENSO, upper ocean heat content anomalies in the North Atlantic which can re-emerge the following winter, Arctic sea-ice cover and the Quasi-Biennial Oscillation (QBO). Improvements in both initialization and model formulation – including horizontal and vertical resolution, as well as the inclusion of the stratosphere in the atmosphere model – are responsible for this improved correlation. However, the NAO correlation is found to increase more slowly with ensemble size than expected, indicating that the models appear to be less

predictable than the real world. This has been termed the “signal-to-noise paradox” (Eade et al., 2014) and is still not fully understood. However, it is hoped that improvements in the areas of non-orographic gravity waves and stochastic physics may play a part in allowing the apparent theoretical NAO correlation, of round 0.8, to be realised without the requirement to have a very large ensemble.

It is important to recognise the role of the ocean data assimilation and operational oceanography communities in providing the initial conditions for such dynamical seasonal forecast systems. These are required both in real time to initialise the seasonal forecasts themselves, and also as reanalyses (see Chapter 19 by Haines) which are needed to initialise the seasonal hindcasts used to calibrate and “bias-correct” information from the real-time system. One of the challenges of seasonal forecasting is to ensure as much consistency as possible between these two different initializations despite a changing observational network. Improvements in mean climate in the coupled atmosphere-ocean models used within seasonal forecasting systems are important to reduce model biases, and therefore reduce the sensitivity to the bias correction and calibration procedure (which can be particularly problematic for variables like sea-ice cover). However, model biases are not likely to be completely eliminated in the foreseeable future, and so a potentially important development is the use of machine learning approaches for the calibration and bias correction of coupled ocean-atmosphere forecasts.

The computational cost of these ensemble seasonal systems, with their accompanying hindcasts, has prevented many operational centres upgrading the ocean resolution from  $1^\circ$  to  $1/4^\circ$  until the last few years. Some of the improvements in the latest UK Met Office GloSea5 system (MacLachlan et al., 2015) have been attributed to the increased ocean resolution – for example, improved Atlantic winter “blocking” due to reduced North Atlantic sea surface temperature (SST) biases at  $1/4^\circ$  (Scaife et al., 2011).

Decadal forecasting is a less mature field than seasonal forecasting, and in this case a key source of predictability is anthropogenic forcing from greenhouse gases and aerosols. Solar variability and volcanic forcing (once an eruption has occurred) provide additional sources of predictability, as do fluctuations of the Atlantic Meridional Overturning Circulation which are potentially predictable a few years ahead (e.g., Griffies and Bryan 1997). In common with seasonal forecasting, the QBO (predictable a couple of years ahead; Marshall and Scaife 2009) and Arctic sea ice provide further potential sources of predictability. Cassou et al. (2018) provides a comprehensive but succinct recent review on decadal variability and predictability.

Decadal forecast systems require coupled models (usually at a similar resolution to seasonal forecast systems) which can represent the ocean circulation well, including aspects such as Nordic sea overflows which are important to maintain the correct ocean water masses. Again, coupled hindcasts are required in order to allow the skill of the system to be assessed and in some cases to bias-correct the real-time forecasts. Initialization of these hindcasts is even more of a challenge than for seasonal forecasting because the timescales require a larger range of start dates to be used (e.g., back to the 1950s). This means the problem of a non-stationary ocean observing system is particularly acute, and also requires the use of a significant pre-Argo period when the deeper ocean, of greater importance to decadal predictability, was very poorly sampled. Using hindcasts for

calibration of the real-time forecasts can also be more problematic because the difference between the coupled model and real-world climatology may vary over time due to climate change. This makes it harder to use hindcasts for bias correction of coupled model drift without masking what is already a smaller predictable signal than on seasonal timescales. As a result, a number of decadal prediction systems have instead used anomaly initialization (Pierce et al., 2004) where observed ocean state anomalies are added to the coupled model climatology. The relationship between model drift and model biases with alternative initialization strategies for decadal forecast systems are discussed and analysed in Sanchez-Gomez et al. (2016); this is an important area of research with the potential to reduce model biases in future. Approaches, like Empirical Orthogonal Functions, to make better use of sparse observations to initialize the historical ocean state are still developing (see Chapter 19 by Haines).

Following the progress in NAO prediction in seasonal forecasting systems, studies using UK Met Office's Decadal Prediction System showed similar correlations for the first winter (for forecasts initialized in November) and a correlation of greater than 0.4 for the second winter (Dunstone et al., 2016).

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### Short- to medium-range (1-2 weeks)

The one-week to two-week timescale is that on which atmosphere-ocean coupled modelling has come to the fore in the operational oceanography and numerical weather prediction communities over the last decade. In fact, for regional modelling, coupled systems can scarcely be considered as “new frontier” given models like the Hurricane Weather Research and Forecast model (Bender et al., 2007) or its predecessors have included an interactive ocean component for close to two decades. More recently, examples of operational regional coupled systems include the Coupled Ocean Atmosphere Mesoscale Prediction System (COAMPS; Chen et al., 2010; Holt et al., 2011) developed at the US Naval Research Laboratory (NRL), and the system (which also includes sea ice) run for the Gulf of St Lawrence and Great Lakes by the Canadian Centre for Meteorological and Environmental Prediction (Pellerin et al., 2004). There are an increasing number of pre-operational and research coupled systems, often using the Coupled Ocean Atmosphere Wave Sediment Transport (COAWST; Warner et al., 2010) framework and its component models: the WRF atmosphere model, the ROMS ocean model, the SWAN wave model and the Community Sediment Transport Model. NRL's COAMPS has also been used in various different domains. In the UK there is active research on a UK Environmental Prediction system which uses a 1.5 km configuration of the Met Office Unified Model coupled to configurations of both the NEMO ocean model and the WaveWatchIII wave model (also at 1.5 km) with the intention of adding additional earth system components at a later date (Lewis et al., 2018).

There are fewer global coupled configurations running at present but Table 16.1 summarises some of those which are either already operational or are planned within the next couple of years. We note here that the coupled system run at the Canadian Centre for Meteorological and Environmental Prediction (CCMEP) is currently the only operational system being used for both ocean forecasting and numerical weather prediction (NWP). The UK Met Office is at present the

only provider of ocean forecasts from a coupled system using (weakly) coupled data assimilation and by 2020 this system is also expected to be used for NWP. The ECMWF operational NWP system will be (partially) coupled from 2018, and at NRL there are ambitious plans for coupled configurations with very high (1/25°) ocean resolution.

Centre	Atmosphere Model (resolution)	Ocean Model (resolution)	Wave Model (resolution)	Coupler	Data Assimilation	Year	Notes
Canadian Centre for Meteorological and Environmental Prediction (CCMEP)	GEM (25 km)	NEMO (1/4 °)	-	GOSSIP (in-house coupler)	Uncoupled	2017	Provides both NWP and ocean forecasts (since 1 Nov 2017)
	<i>GEM (15 km)</i>	<i>NEMO (1/4 °)</i>	-	<i>GOSSIP</i>	<i>Uncoupled</i>	<i>2018</i>	
European Centre for Medium Range Weather Forecasting (ECMWF)	IFS (9 km)	NEMO (1/4 °)	WAM (1/8 °)	Single executable	Uncoupled	2018	Partial coupling (full coupling in tropics)
UK Met Office	UM (40 km)	NEMO (1/4 °)	-	OASIS3	Weakly coupled	2017	Provides ocean forecasts to Copernicus Marine Service (since 11 Jul 2017)
	<i>UM (10 km)</i>	<i>NEMO (1/4 °)</i>	<i>WWIII [if used]</i>	<i>OASIS3-MCT</i>	<i>Weakly coupled</i>	<i>2020</i>	<i>Planned for NWP use; wave model may be included (not confirmed)</i>
US Naval Research Laboratory (NRL)	NAVGEN (19 km)	HYCOM (1/25 °)	WAM (1/8 °)	ESMF / NUOPC	Weakly coupled	2019	This is the “Initial Operational Capability”; final capability (2022) will have a higher resolution atmosphere and strongly coupled DA

**Table 16.1.** Summary of current and next planned (*in italics*) operational global coupled atmosphere-ocean systems at various national centres.

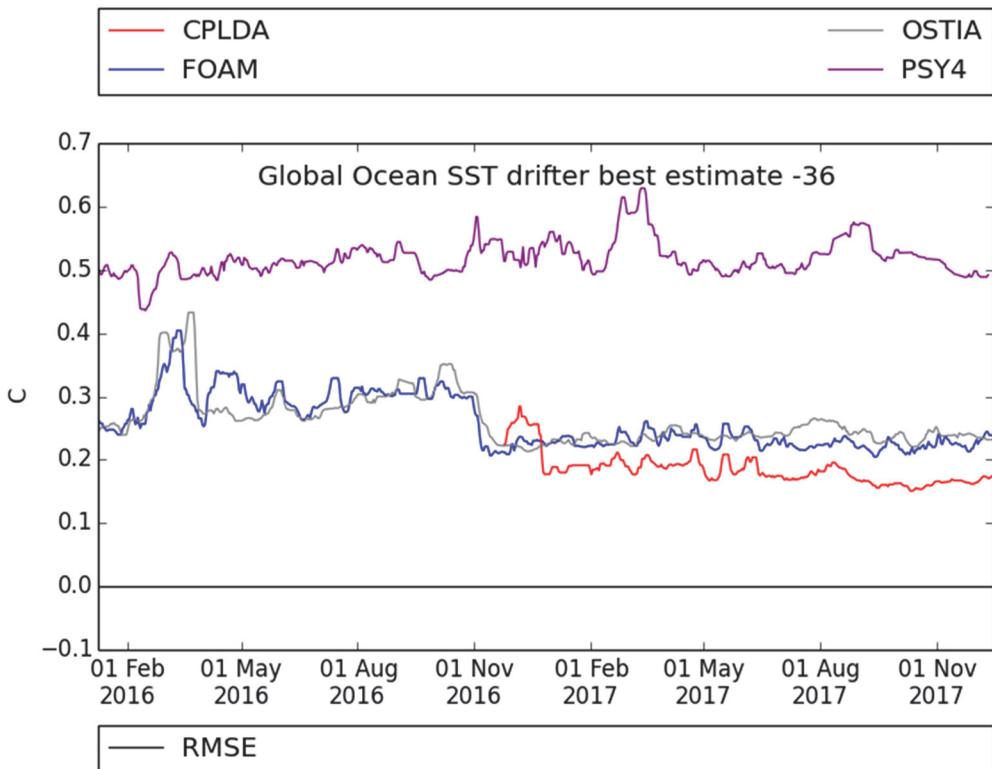
Almost all of these operational systems, or pre-operational research systems, have been able to demonstrate improvements on tropical weather and ocean forecasts. The most notable impact is on tropical cyclones where systems with an “NWP-resolution” atmosphere model have shown reductions in track errors as well as a moderation of the tendency to over-deepen storms now seen in many atmosphere-only NWP systems. This is associated with the development of a “cold wake” of sea surface temperatures which does not exist in a persisted SST analysis (and in fact may take several days to be properly represented in such an analysis due to cloud limitations in satellite retrievals; Mogensen et al., 2017). There is further work required to improve tropical storm responses in such global coupled systems because most atmosphere models – including the Unified Model configuration used in the UK Met Office NWP system, and IFS used at ECMWF – underestimate the wind strength for a given central pressure in these storms. Addressing this, while not causing excessive ocean mixing and upwelling which then weakens the storms too much, will most likely require improvements to the bulk formulae used to calculate the turbulent fluxes, and the way waves are modelled and coupled.

In a version of their deterministic operational model which was coupled to an ocean (in the tropics only), ECMWF have seen a ~10% reduction in 5-day forecast surface pressure and 500 hPa root-mean-square (rms) errors in the tropics. Smaller, but still statistically significant, improvements in winds and relative humidity from the surface up to 100 hPa were also seen (Balsamo et al., 2017). The Canadian GIOPS system has also shown similar improvements, apparently driven by improved latent heat fluxes and more realistic pumping of heat and moisture in the atmosphere (Smith et al., 2018).

Aside from resolution, one of the major differences between the operational coupled global systems shown in Table 16.1 is their approach to initialization. As on the longer timescales already discussed this is a significant challenge, but the focus is now on the avoidance of the initialization shocks mentioned earlier. Most centres are now pursuing research into coupled data assimilation. In its “weakly coupled” form, this means observations in one component can influence other components only through the background state or in some cases the outer loop (see Chapter 17 by Hoteit et al.). More “strongly coupled” data assimilation makes use of “cross-interface” covariances which allow observations in the atmosphere to directly influence the ocean and vice versa. As already mentioned, the UK Met Office coupled system is the only operational real-time system making use of (weakly) coupled data assimilation. In part this is possible because the atmosphere resolution is relatively low and it has therefore been possible to find a way of dealing with the latency of ocean observations (involving “catch-up” sub-cycles producing updated analyses) which is not prohibitively expensive. The weakly coupled data assimilation system used at the Met Office has been shown to produce ocean analyses (and short lead-time forecasts) with smaller sea surface temperature rms errors than those in the equivalent ocean-only FOAM system (see Fig. 16.2). In addition, the mean SST increments are found to be smaller than in an equivalent ocean-only analysis indicating that the ocean state is more consistent with the atmospheric forcing (Lea et al., 2015).

ECMWF and CCMEP are both running higher resolution atmosphere configurations, and have for the moment taken different approaches to reducing initialization shock without the immediate

need for coupled data assimilation – instead the component models are initialized separately using their own analysis systems. The CCMEP system is careful to ensure as much consistency as possible between the atmospheric and oceanic boundary layers by using the same bulk formulae in both atmosphere and ocean, and assimilating the same SST product into the ocean analysis as is used for the atmospheric surface boundary. ECMWF instead use “full coupling” only in the tropics, and at higher latitudes apply a “partial coupling” whereby the atmosphere model sees an SST analysis combined with tendencies from the ocean model during the first week of the forecast. As well as reducing the likelihood of initialization shocks, this means the atmosphere model is not immediately exposed to sea surface temperature biases associated with an incorrect Gulf Stream position – a feature of most current ocean models, particularly at  $1/4^\circ$  resolution or lower.



**Figure 16. 2.** Root-mean-square errors (RMSE) in degrees Celsius of “best estimate” sea surface temperature analyses verified using the class4 methodology (see Chapter 29 by Hernandez et al.) against in-situ observations from drifting buoys. The UK Met Office weakly coupled data assimilation system (red) is compared against the operational ocean-only FOAM system (blue) and the OSTIA sea surface temperature analysis product (grey). A 10-day rolling median of globally averaged values is shown.

For ocean forecasting, there is again often a “resolution versus complexity” debate whereby a high-resolution (and eddy-resolving) ocean configuration is compared to a coupled atmosphere-ocean system with a lower (eddy-permitting) ocean resolution. In fact, the results seen in high-resolution coupled climate simulations suggest this is an artificial debate: for the benefits of coupling to be more fully seen then an eddy-resolving ocean (and comparable atmosphere resolution) is required. An obvious next step in the development of short-range coupled systems is

therefore an increase of ocean resolution to match the leading eddy-resolving global systems and so allow the mesoscale and frontal coupling to the atmosphere to be better represented. This is planned at centres including the US Naval Research Laboratory and the UK Met Office within the next few years and will be accompanied by further research to allow a move beyond independent (or at best “weakly coupled”) analyses for initialization. Research is also required into how to make best use of (lower resolution) coupled ensembles in order to provide flow-dependent information for improving the ocean data assimilation in a hybrid variational system.

Arguably the shortest of all short-range “forecasts” are reanalyses which only perform the data assimilation step in order to provide estimates of historical atmosphere or ocean states, but using the latest models and data assimilation codes (see Chapter 19 by Haines). Coupled data assimilation has progressed more quickly in this context, in part because there are not the real-time complications associated with late arriving ocean observations (or orbit corrections to altimetry – see Chapter 7 by Le Traon). Although ocean resolutions utilised have been relatively low – for example 1° deg for both ECDA at GFDL (Chang et al., 2013) and for CERA-20C at ECMWF (Laloyaux et al., 2016; Laloyaux et al., 2018) – coupled reanalyses have been found to improve the surface fluxes and reduce the ocean increments compared to their ocean-only counterparts (see Chapter 19 by Haines).

## Applications of Coupled Modelling for Different Timescales

As with all forms of ocean and atmosphere modelling, there is only value to users, and to society in general, when the systems developed can be applied to real-world decision making. Here we briefly outline applications of coupled systems on the various timescales.

### Climate

For the last three decades, the Intergovernmental Panel on Climate Change (IPCC) have reported regularly not only on the most likely changes in climate over the coming century, but also on the impacts of these future climate changes. Multi-model ensembles are used to provide some kind of estimate of the uncertainty of these projections, which are also based on assumptions derived from various possible emission pathways and potential mitigation measures. As part of CMIP6 (Eyring et al., 2016) a number of “Shared Socio-economic Pathways” have been developed covering plausible but different socio-economic, political and technological futures (O’Neill et al., 2017).

Particularly when using early climate models (with atmospheric resolution in the hundreds of km) it was difficult to make confident statements about regional climate changes and impacts (especially those related to extreme events) even if the projected large-scale climate change was assumed to be reliable. Other impacts like sea level rise are not directly predicted by the Boussinesq (i.e. volume-conserving) ocean models most frequently used and have to be inferred indirectly. However, initiatives like the “four degree map” (Met Office 2018a) produced by the UK Met Office at the time of the IPCC Fourth Assessment Report (AR4) have attempted to summarize likely

impacts of a four degree rise in global mean temperatures, albeit based on a relatively low resolution climate model (HadCM3; Gordon et al., 2000).

More recently the effort devoted to assessing the socio-economic impact of potential changes in regional climate has increased significantly. In general, this still requires down-scaling techniques to obtain information on more local scales. Sophisticated statistical techniques are used, in combination with ensembles of global models, to provide probabilistic information – for example, on seasonal mean and extreme changes in temperature and precipitation, in a variety of different emissions scenarios. Recent initiatives have included UK Climate Projections 09 (Met Office 2018b) which included a marine and coastal report. These projections are being updated in 2018 to include down-scaling using a cutting-edge 2.2 km atmospheric configuration, and similar work is now being started as part of the European Union Climate Projections. Resolution increases in global climate models (as described in the previous section) bring these closer to being able to simulate realistic local “weather” in a future climate. However, the requirement to assess uncertainties in regional projections of climate change and impacts means that down-scaling is likely to have an important role for the foreseeable future. The increased complexity and additional components in the Earth system models described in the previous section will allow more impacts to be predicted directly. They will also provide more confidence in changes caused by anthropogenic greenhouse gas emissions and, for example, melting of land ice and ice shelves.

Many of these impacts and applications are encompassed by what have become known as “climate services”. This is a term with a broad meaning but is defined by the European Commission Climate Service (European Commission 2018) as “transforming climate-related data and other information into customised products such as projections, trends, economic analysis, advice on best practices, development and evaluation of solutions, and any other climate-related service liable to benefit that may be of use for the society.” These services include data, information and knowledge that support adaptation, mitigation and disaster risk management on both climate and seasonal timescales.

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## Seasonal and decadal

The maturity of seasonal forecasting in the tropics, using both dynamical and statistical models, is such that predictions of ENSO, and impacts with teleconnections to ENSO, have been made for some time. Predictions have been made publicly available alongside other seasonal forecast information by the World Meteorological Centre Global Producing Centres (WMO 2018), and more recently as part of initiatives like the newly established Copernicus Climate Service in Europe (C3S 2018). Predictions of North Atlantic tropical cyclone activity (both number of storms, and accumulated cyclone energy over the June to November hurricane season) have also been shown to have statistically significant skill in recent years (e.g., Camp et al., 2015). This is despite the relatively low atmospheric resolution (~50 km) which is not nearly sufficient to represent realistic tropical storms. The Met Office decadal prediction system has also been able to demonstrate skill in predicting Atlantic tropical cyclone activity with lead times of several years. Probabilistic

forecasts of this nature, on both one year and multi-year timescales, are of significant value, particularly for the insurance and re-insurance industries.

Recent successes in improving NAO predictability from seasonal forecast systems have opened the door for a wide of range new applications and services. At present these services largely make use of previously known, or newly identified, correlations between specific impacts and the observed winter NAO; they then use the skill in NAO predictions to show skilful predictions of these impacts. There are various reasons why the impacts themselves are often not directly predicted from the seasonal forecast model output including lack of sufficient resolution or complexity to represent the impact in the modelling system (particularly for extremes or local effects). In addition, there may be complications caused by the need to bias-correct seasonal forecast output, and difficulties due to the low signal-to-noise ratio described in x.2.2. Examples of applications where skilful winter forecasts have been shown include UK river flow (Svensson et al., 2015) and transport disruption (Palin et al., 2015), European energy demand (Clark et al., 2017) and Baltic Sea ice (Karpechko et al., 2015). In other cases, direct correlations between seasonal forecasts output and observed impacts have been identified and used to show skilful prediction of, for example, Yangtze rainfall and river flow (Li et al., 2016) and energy demand and potential renewable energy supply, from solar and wind power, in parts of China (Bett et al., 2017).

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## Short- to Medium-Range

The majority of the applications on short timescales are similar to those using traditional forecasting systems, albeit with some improvements in skill which may over time open up potential for new products.

Clearly more accurate forecasting of tropical storms, and particularly their tracks, is potentially of great significance. Information from deterministic models will always be of limited value and so it will be as ensembles of coupled atmosphere-ocean models start to be more routinely used that more of the benefit is realised. Some of the most beneficial impacts of coupled models for warnings and other impacts will come from the high-resolution regional coupled systems being developed. These will allow more accurate information about coupled extremes on a local basis, as well as benefitting from any improvements in lateral boundary conditions due to coupling in global, or basin-scale, models. For example, coastal flooding around the UK can be strongly affected by sea state, storm surges, and river inputs, and is therefore determined by a complex interaction of meteorology, oceanography and land-surface and hydrological processes. As more earth system components are added to these regional coupled systems then, in combination with very high resolution downscaling or nesting very close to the coast, the potential for providing improved predictions will increase. COAWST-based systems have already been used for a range of operational and research applications in different regional domains including coastal zone management, oil-spill dispersion modelling, coastal morphology changes during storms, sediment transport, egg and larvae dispersal, and hypoxic events (see e.g. Carniel et al., 2013). Other very specific applications of coupled modelling include The Balearic RIssaga Forecasting System (BRIFS) which uses a high-resolution ROMS configuration coupled to a WRF atmosphere with the

aim of quantitatively predicting the occurrence of extreme sea level oscillations associated with meteo-tsunami in the Menorcan harbour of Ciutadella (Licer et al., 2017).

Coupled analysis (or reanalysis) and forecast systems also have the advantage of providing fully consistent surface meteorology, sea state and surface ocean products. For some users having a fully consistent coupled climatology to use in downstream statistical models may be an additional benefit. Any improvements in the ocean sub-surface which can be obtained in coupled (re)analyses are also likely to improve predictability on seasonal timescales when used for initialising seasonal hindcasts and forecasts.

## Concluding Comments

This chapter has provided a selective summary of coupled atmosphere–ocean modelling on various timescales, with a particular focus on short-range global predictions. Both recent successes and some of the remaining challenges have been presented.

A common question is whether we should expect that all ocean-only systems, even for short-range forecasts, will ultimately be replaced by coupled systems. It seems very unlikely that this will happen in the foreseeable future as it will always be possible to use higher resolution in an ocean-only system than an equivalent system coupled to an atmosphere model. At least until it is possible to routinely run global coupled atmosphere–ocean models which resolve the ocean sub-mesoscale there would appear to be a clear role for ocean-only systems. However, we would expect the use of coupled models to continue to increase. Depending on application and timescale this will involve both coupled global models (e.g. climate models) being used to drive high-resolution, uncoupled down-scalers, as well as uncoupled global models being used to provide boundary conditions for high-resolution, regional coupled environmental prediction systems.

Individual operational centres will therefore make different decisions on the priority of coupling in different systems, depending on their remit and user requirements. Most users will not be concerned about whether a particular forecast output was produced from a coupled or uncoupled system; they may be more concerned about a “coupled” delivery of data from multiple model components. However, this will inevitably highlight any inconsistencies between model output which may be problematic for some users. Provision of ocean, atmosphere (as well as wave and sea-ice) data from a single coupled system is the easiest way of providing a fully consistent set of analysis and forecast data, aside from the demonstrated benefits in product quality which can be realised in a coupled system.

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## References

- Balsamo, G., K. Mogensen, S. Keeley, J.-R. Bidlot, S. Boussetta, E. Dutra, and N. Wedi, 2017: Coupling of oceans and land surfaces in the ECMWF Integrated Forecasting System: Sensitivity and impact of diurnal and synoptic variability on medium-range skill. *WGENE Blue Book 2017*, E. Astakhova, Ed., WMO, [http://bluebook.meteoinfo.ru/uploads/2017/docs/09\\_Balsamo\\_Gianpaolo\\_CouplingOceansLandECMWF.pdf](http://bluebook.meteoinfo.ru/uploads/2017/docs/09_Balsamo_Gianpaolo_CouplingOceansLandECMWF.pdf).
- Beljaars, A., E. Dutra, G. Balsamo, and F. Lemarié, 2017: On the numerical stability of surface–atmosphere coupling in weather and climate models, *Geoscientific Model Development*, **10**, 977–989, doi:10.5194/gmd-10-977-2017.
- Bender, M.A., I. Ginis, R. Tuleya, B. Thomas, and T. Marchok, 2007: The operational GFDL coupled hurricane-ocean prediction system and summary of its performance. *Monthly Weather Review*, **135**, 3965–3989, doi: 10.1175/2007MWR2032.1.
- Bett, P., H. Thornton, J. Lockwood, A. Scaife, N. Golding, C. Hewitt, R. Zhu, P. Zhang, and C. Li, 2017: Skill and reliability of seasonal forecasts for the Chinese energy sector. *Journal of Applied Meteorology and Climatology*, doi:10.1175/jamc-d-17-0070.1.
- Brown, A., S. Milton, M. Cullen, B. Golding, J. Mitchell, and A. Shelly, 2012: Unified Modeling and Prediction of Weather and Climate: A 25-Year Journey. *Bulletin of the American Meteorological Society*, **93**, 1865–1877, doi:10.1175/bams-d-12-00018.1.
- Bryan, F., R. Tomas, J. Dennis, D. Chelton, N. Loeb, and J. McClean, 2010: Frontal Scale Air–Sea Interaction in High-Resolution Coupled Climate Models. *Journal of Climate*, **23**, 6277–6291, doi:10.1175/2010jcli3665.1.
- C3S, 2018: Copernicus Climate Change Service. Accessed 5 January 2018, <https://climate.copernicus.eu>.
- Camp, J., M. Roberts, C. MacLachlan, E. Wallace, L. Hermanson, A. Brookshaw, A. Arribas, and A. Scaife, 2015: Seasonal forecasting of tropical storms using the Met Office GloSea5 seasonal forecast system. *Quarterly Journal of the Royal Meteorological Society*, **141**, 2206–2219, doi:10.1002/qj.2516.
- Carniel, S., and A. Russo, 2013: A review of modeling applications using ROMS model and COAWST system in the Adriatic Sea region. <https://arxiv.org/abs/1309.7600>.
- Cassou, C., Y. Kushnir, E. Hawkins, A. Pirani, F. Kucharski, I. Kang, and N. Caltabiano, 2018: Decadal Climate Variability and Predictability: Challenges and Opportunities. *Bulletin of the American Meteorological Society*, **99**(3), 479–490, doi:10.1175/BAMS-D-16-0286.1.
- Chang, Y., S. Zhang, A. Rosati, T. Delworth, and W. Stern, 2012: An assessment of oceanic variability for 1960–2010 from the GFDL ensemble coupled data assimilation. *Climate Dynamics*, **40**, 775–803, doi:10.1007/s00382-012-1412-2.
- Chassignet, E., and X. Xu, 2017: Impact of Horizontal Resolution ( $1/12^\circ$  to  $1/50^\circ$ ) on Gulf Stream Separation, Penetration, and Variability. *Journal of Physical Oceanography*, **47**, 1999–2021, doi:10.1175/jpo-d-17-0031.1.
- Chelton, D.B., and S.-P. Xie, 2010: Coupled ocean-atmosphere interaction at oceanic mesoscales. *Oceanography*, **23**(4), 52–69, doi:10.5670/oceanog.2010.05.
- Chen, S., T. Campbell, H. Jin, S. Gaberšek, R. Hodur, and P. Martin, 2010: Effect of Two-Way Air–Sea Coupling in High and Low Wind Speed Regimes. *Monthly Weather Review*, **138**, 3579–3602, doi:10.1175/2009mwr3119.1.
- Clark, R., P. Bett, H. Thornton, and A. Scaife, 2017: Skilful seasonal predictions for the European energy industry. *Environmental Research Letters*, **12**, 024002, doi:10.1088/1748-9326/aa57ab.
- Craig A., S. Valcke, and L. Coquart, 2017: Development and performance of a new version of the OASIS coupler, OASIS3-MCT\_3.0, *Geoscientific Model Development*, **10**, 3297–3308, doi:10.5194/gmd-10-3297-2017.
- Debreu, L., C. Vouland, and E. Blayo, 2008: Agrif: Adaptive grid refinement in Fortran. *Computers and Geosciences*, **34**, 8–13.
- DeLuca C., G. Theurich, and V. Balaji, 2012: The Earth System Modeling Framework. *Earth System Modelling - Volume 3*, SpringerBriefs in Earth System Sciences, Springer, Berlin, Heidelberg, doi: 10.1007/978-3-642-23360-9\_6
- Delworth, T. L., et al., 2006: GFDL’s CM2 global coupled climate models. Part I: Formulation and simulation. *Journal of Climate*, **19**, 643–674, doi:10.1175/JCLI3629.1.

- Dunstone, N., D. Smith, A. Scaife, L. Hermanson, R. Eade, N. Robinson, M. Andrews, and J. Knight, 2016: Skilful predictions of the winter North Atlantic Oscillation one year ahead. *Nature Geoscience*, **9**, 809–814, doi:10.1038/ngeo2824.
- Eade, R., D. Smith, A. Scaife, E. Wallace, N. Dunstone, L. Hermanson, and N. Robinson, 2014: Do seasonal-to-decadal climate predictions underestimate the predictability of the real world? *Geophysical Research Letters*, **41**, 5620–5628, doi:10.1002/2014gl061146.
- European Commission, 2018: Climate Services. Accessed 5 January 2018, [https://ec.europa.eu/research/environment/index.cfm?pg=climate\\_services](https://ec.europa.eu/research/environment/index.cfm?pg=climate_services).
- Eyring, V., S. Bony, G. A. Meehl, C. A. Senior, B. Stevens, R. J. Stouffer, and K. E. Taylor, 2016: Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, *Geoscientific Model Development*, **9**, 1937–1958, doi:10.5194/gmd-9-1937-2016.
- Gent, P., and J. McWilliams, 1990: Isopycnal Mixing in Ocean Circulation Models. *Journal of Physical Oceanography*, **20**, 150–155, doi:10.1175/1520-0485(1990)020<0150:imiocm>2.0.co;2.
- Gent, P. R., G. Danabasoglu, L. J. Donner, M. M. Holland, E. C. Hunke, S. R. Jayne, D. M. Lawrence, R. B. Neale, P. J. Rasch, M. Vertenstein, P. H. Worley, Z.-L. Yang, and Z. Minghua, 2011: The Community Climate System Model Version 4, *Journal of Climate*, **24** (19), 4973–4991, doi:10.1175/2011JCLI4083.1.
- Gent, P. R., S. G. Yeager, R. B. Neale, S. Levis, and D. A. Bailey, 2009: Improvements in a half degree atmosphere/land version of the CCSM. *Climate Dynamics*, **34**, 819–833.
- Gordon, C., C. Cooper, C. A. Senior, H. Banks, J. M. Gregory, T. C. Johns, J. F. B. Mitchell, and R. A. Wood, 2000: The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments. *Climate Dynamics*, **16** (2–3), 147–168, doi:10.1007/s003820050010.
- Griffies, S., and K. Bryan, 1997: A predictability study of simulated North Atlantic multidecadal variability. *Climate Dynamics*, **13**, 459–487, doi:10.1007/s003820050177.
- Griffies, S. et al., 2009: Coordinated Ocean-ice Reference Experiments (COREs). *Ocean Modelling*, **26**, 1–46, doi:10.1016/j.ocemod.2008.08.007.
- Griffies, S., M. Winton, W. G. Anderson, R. Benson, T. L. Delworth, C. O. Dufour, J. P. Dunne, P. Goddard, A. K. Morrison, A. Rosati, A. T. Wittenberg, J. Yin, and R. Zhang, 2015: Impacts on Ocean Heat from Transient Mesoscale Eddies in a Hierarchy of Climate Models. *Journal of Climate*, **28**, 952–977, doi:10.1175/jcli-d-14-00353.1.
- Haarsma, R. et al., 2016: High Resolution Model Intercomparison Project (HighResMIP v1.0) for CMIP6. *Geoscientific Model Development*, **9**, 4185–4208, doi:10.5194/gmd-9-4185-2016.
- Hazeleger W. et al., 2010: EC-Earth: a seamless earth system prediction approach in action. *Bulletin American Meteorological Society*, **91**, 1357–1363, doi:10.1175/2010BAMS2877.1.
- Hermanson, L., H.-L. Ren, M. Vellinga, N. D. Dunstone, P. Hyder, S. Ineson, A. A. Scaife, D. M. Smith, V. Thompson, B. Tian, and K. D. Williams, 2017: Different types of drifts in two seasonal forecast systems and their dependence on ENSO. *Climate Dynamics*, doi:10.1007/s00382-017-3962-9.
- Hewitt H., D. Copey, I. D. Culverwell, C. M. Harris, R. S. R. Hill, A. B. Keen, A. J. McLaren, and E. C. Hunke, 2011: Design and implementation of the infrastructure of HadGEM3: the next-generation Met Office climate modelling system, *Geoscientific Model Development*, **4**, 223–253, doi:10.5194/gmd-4-223-2011.
- Hewitt, H. et al., 2016: The impact of resolving the Rossby radius at mid-latitudes in the ocean: results from a high-resolution version of the Met Office GC2 coupled model. *Geoscientific Model Development*, **9**, 3655–3670, doi:10.5194/gmd-9-3655-2016.
- Hewitt, H., M. J. Bell, E. P. Chassignet, A. Czaja, D. Ferreira, S. M. Griffies, P. Hyder, J. McClean, A. L. New, and M. J. Roberts, 2017: Will high-resolution global ocean models benefit coupled predictions on short-range to climate timescales? *Ocean Modelling*, doi:10.1016/j.ocemod.2017.11.002.
- Holt, T., J. Cummings, C. Bishop, J. Doyle, X. Hong, S. Chen, and Y. Jin, 2011: Development and testing of a coupled ocean–atmosphere mesoscale ensemble prediction system. *Ocean Dynamics*, **61**, 1937–1954, doi:10.1007/s10236-011-0449-9.
- Hurrell, J., G. Meehl, D. Bader, T. Delworth, B. Kirtman, and B. Wielicki, 2009: A Unified Modeling Approach to Climate System Prediction. *Bulletin of the American Meteorological Society*, **90**, 1819–1832, doi:10.1175/2009bams2752.1.
- Kirtman, B. P., C. Bitz, F. Bryan, W. Collins, J. Dennis, N. Hearn, J. L. KinterIII, R. Loft, C. Rousset, L. Siqueira, C. Stan, R. Tomas and M. Vertenstein, 2012: Impact of ocean model resolution on CCSM climate simulations. *Climate Dynamics*, **39**, 1303–1328, doi:10.1007/s00382-012-1500-3.
- Lalouaux, P., M. Balmaseda, D. Dee, K. Mogensen, and P. Janssen, 2016: A coupled data assimilation system for climate reanalysis. *Quarterly Journal of the Royal Meteorological Society*, **142**: 65–78. doi:10.1002/qj.2629

- Laloyaux, P., E. de Boisseson, M. Balmaseda, J.-R. Bidlot, S. Broennimann, R. Buizza, P. Dahlgren, D. Dee, L. Haimberger, H. Hersbach, Y. Kosaka, M. Martin, P. Poli, N. Rayner, E. Rustemeier and D. Schepers, 2018: CERA-20C: A coupled reanalysis of the Twentieth Century. *Journal of Advances in Modeling Earth Systems*, Accepted, doi:10.1029/2018MS001273.
- Lea, D., I. Mirouze, M. Martin, R. King, A. Hines, D. Walters, and M. Thurlow, 2015: Assessing a New Coupled Data Assimilation System Based on the Met Office Coupled Atmosphere–Land–Ocean–Sea Ice Model. *Monthly Weather Review*, **143**, 4678–4694, doi:10.1175/mwr-d-15-0174.1.
- Lemarié, F., E. Blayo, and L. Debreu, 2015: Analysis of ocean-atmosphere coupling algorithms: consistency and stability. *Procedia Computer Science*, **51**, 2066–2075, doi:10.1016/j.procs.2015.05.473.
- Lewis, H. et al., 2018: The UKC2 regional coupled environmental prediction system. *Geoscientific Model Development*, **11**, 1–42, doi:10.5194/gmd-11-1-2018.
- Ličer, M., B. Mourre, C. Troupin, A. Kriemeyer, A. Jansá, and J. Tintoré, 2017: Numerical study of Balearic meteotsunami generation and propagation under synthetic gravity wave forcing. *Ocean Modelling*, **111**, 38–45, doi:10.1016/j.ocemod.2017.02.001.
- MacLachlan, C., A. Arribas, K. A. Peterson, A. Maidens, D. Fereday, A. A. Scaife, M. Gordon, M. Vellinga, A. Williams, R. E. Comer, J. Camp, P. Xavier, and G. Madec, 2014: Global Seasonal forecast system version 5 (GloSea5): a high-resolution seasonal forecast system. *Quarterly Journal of the Royal Meteorological Society*, **141**, 1072–1084, doi:10.1002/qj.2396.
- Magnusson, L., M. Alonso-Balmaseda, and F. Molteni, 2012: On the dependence of ENSO simulation on the coupled model mean state. *Climate Dynamics*, **41**, 1509–1525, doi:10.1007/s00382-012-1574-y.
- Marshall, A., and A. Scaife, 2009: Impact of the QBO on surface winter climate. *Journal of Geophysical Research*, **114**, doi:10.1029/2009jd011737.
- Met Office, 2018a: The impact of four degree temperature rise. Accessed 5 January 2018, <https://www.metoffice.gov.uk/climate-guide/climate-change/impacts/four-degree-rise>
- Met Office, 2018b: UK Climate Projections. Accessed 5 January 2018, <http://ukclimateprojections.metoffice.gov.uk>.
- Minobe, S., A. Kuwano-Yoshida, N. Komori, S. Xie, and R. Small, 2008: Influence of the Gulf Stream on the troposphere. *Nature*, **452**, 206–209, doi:10.1038/nature06690.
- Mogensen, K., L. Magnusson, and J. Bidlot, 2017: Tropical cyclone sensitivity to ocean coupling in the ECMWF coupled model. *Journal of Geophysical Research: Oceans*, **122**, 4392–4412, doi:10.1002/2017jc012753.
- Mulholland, D. P., P. Laloyaux, K. Haines and M. A. Balmaseda, 2015: Origin and Impact of Initialization Shocks in Coupled Atmosphere–Ocean Forecasts. *Monthly Weather Review*, **143**, 4631–4644, doi:10.1175/MWR-D-15-0076.1.
- O’Neill, B. C., E. Kriegler, K. L. Ebi, E. Kemp-Benedict, K. Riahi, D. S. Rothman, B. J. van Ruijven, D. P. van Vuuren, J. Birkmann, K. Kok, M. Levy, and W. Solecki. 2017: The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*, **42**, 169–180, doi:10.1016/j.gloenvcha.2015.01.004.
- Palin, E., A. Scaife, E. Wallace, E. Pope, A. Arribas, and A. Brookshaw, 2016: Skillful Seasonal Forecasts of Winter Disruption to the U.K. Transport System. *Journal of Applied Meteorology and Climatology*, **55**, 325–344, doi:10.1175/jamc-d-15-0102.1.
- Parfitt, R., A. Czaja, S. Minobe, and A. Kuwano-Yoshida, 2016: The atmospheric frontal response to SST perturbations in the Gulf Stream region. *Geophysical Research Letters*, **43**, 2299–2306, doi:10.1002/2016gl067723.
- Parfitt, R., A. Czaja, and Y. Kwon, 2017: The impact of SST resolution change in the ERA-Interim reanalysis on wintertime Gulf Stream frontal air-sea interaction. *Geophysical Research Letters*, **44**, 3246–3254, doi:10.1002/2017gl073028.
- Pellerin, P., H. Ritchie, F. J. Saucier, F. Roy, S. Desjardins, M. Valin, and V. Lee, 2004: Impact of a two-way coupling between an atmospheric and an ocean-ice model over the Gulf of St. Lawrence. *Monthly Weather Review*, **132**(6), 1379–1398, doi:10.1175/1520-8810(2004)132<1379:IOATCB>2.0.CO;2.
- Pierce D. W., T. P. Barnett, R. Tokmakian, A. Semtner, M. Maltrud, J. Lysne, and A. Craig, 2004: The ACPI project, element 1: initializing a coupled climate model from observed initial conditions. *Climate Change*, **62**, 13–28, doi:10.1023/B:CLIM.0000013676.42672.23.
- PRIMAVERA, 2018. Accessed 5 January 2018, <https://www.primavera-h2020.eu/>.
- Renault, L., J. Molemaker, J. McWilliams, A. Shchepetkin, F. Lemarié, D. Chelton, S. Illig, and A. Hall, 2016: Modulation of wind-work by oceanic current interaction with the atmosphere. *Journal of Physical Oceanography*, **46**, 1685–1704, doi:10.1175/JPO-D-15-0232.1.

- Roberts, M., H. Hewitt, P. Hyder, D. Ferreira, S. Josey, M. Mizielinski, and A. Shelly, 2016: Impact of ocean resolution on coupled air-sea fluxes and large-scale climate. *Geophysical Research Letters*, **43**, 10,430–10,438, doi:10.1002/2016gl070559.
- Sanchez-Gomez, E., C. Cassou, Y. Ruprich-Robert, E. Fernandez, and L. Terray, 2016: Drift dynamics in a coupled model initialized for decadal forecasts. *Climate Dynamics*, **46**, 1819–1840, doi:10.1007/s00382-015-2678-y.
- Scaife, A., D. Copesey, C. Gordon, C. Harris, T. Hinton, S. Keeley, A. O'Neill, M. Roberts, and K. Williams, 2011: Improved Atlantic winter blocking in a climate model. *Geophysical Research Letters*, **38**, doi:10.1029/2011gl049573.
- Scaife, A., A. Arribas, E. Blockley, A. Brookshaw, R. T. Clark, N. Dunstone, R. Eade, D. Fereday, C. K. Folland, M. Gordon, L. Hermanson, J. R. Knight, D. J. Lea, C. MacLachlan, M. Martin, A. K. Peterson, D. Smith, M. Vellinga, E. Wallace, J. Waters and A. Williams, 2014: Skillful long-range prediction of European and North American winters. *Geophysical Research Letters*, **41**, 2514–2519, doi:10.1002/2014gl059637.
- Shaffrey, L. et al., 2009: U.K. HiGEM: The New U.K. High-Resolution Global Environment Model—Model Description and Basic Evaluation. *Journal of Climate*, **22**, 1861–1896, doi:10.1175/2008jcli2508.1.
- Smith, D., R. Eade, and H. Pohlmann, 2013: A comparison of full-field and anomaly initialization for seasonal to decadal climate prediction. *Climate Dynamics*, **41**, 3325–3338, doi:10.1007/s00382-013-1683-2.
- Smith, D., R. Eade, N. Dunstone, D. Fereday, J. Murphy, H. Pohlmann, and A. Scaife, 2010: Skillful multi-year predictions of Atlantic hurricane frequency. *Nature Geoscience*, **3**, 846–849, doi:10.1038/ngeo1004.
- Smith, G. C., J.-M. Bélanger, F. Roy, P. Pellerin, H. Ritchie, K. Onu, M. Roch, A. Zadra, D. Surcel Colan, B. Winter, J.-S. Fontecilla and D. Deacu, 2018: Impact of Coupling with an Ice-Ocean Model on Global Medium-Range NWP Forecast Skill, *Monthly Weather Review*, **146**, 1157–1180, doi:10.1175/MWR-D-17-0157.1.
- Svensson, C. et al., 2015: Long-range forecasts of UK winter hydrology. *Environmental Research Letters*, **10**, 064006, doi:10.1088/1748-9326/10/6/064006.
- Warner, J., B. Armstrong, R. He, and J. Zambon, 2010: Development of a Coupled Ocean–Atmosphere–Wave–Sediment Transport (COAWST) Modeling System. *Ocean Modelling*, **35**, 230–244, doi:10.1016/j.ocemod.2010.07.010.
- Weisheimer, A., N. Schaller, C. O'Reilly, D. A. MacLeod, and T. Palmer, 2017: Atmospheric seasonal forecasts of the twentieth century: multi-decadal variability in predictive skill of the winter North Atlantic Oscillation (NAO) and their potential value for extreme event attribution. *Quarterly Journal of the Royal Meteorological Society*, **143**, 917–926. doi:10.1002/qj.2976
- West A., A. J. McLaren, H. T. Hewitt, and M. J. Best, 2016: The location of the thermodynamic atmosphere–ice interface in fully coupled models – a case study using JULES and CICE. *Geoscientific Model Development*, **9**, 1125–1141, doi:10.5194/gmd-9-1125-2016.
- WMO, 2018: Global Producing Centres. Accessed 5 January 2018, <http://www.wmo.int/pages/prog/wcp/wcasp/gpc/gpc.php>.
- Yu Karpechko, A., K. Andrew Peterson, A. Scaife, J. Vainio, and H. Gregow, 2015: Skillful seasonal predictions of Baltic Sea ice cover. *Environmental Research Letters*, **10**, 044007, doi:10.1088/1748-9326/10/4/044007.



