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Ensemble Methods: Nowcasting to Climate Change - Abstracts of the Bureau of Meteorology Annual R&D Workshop, 26th November to 30th November 2018, Melbourne, Australia

Keith Day, Michael Naughton, Saima Aijaz, Surendra Rauniyar, Grant Smith, Carlos Velasco-Forero and Meelis Zidikheri (editors)

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Bureau Research Report - 030

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Contents

FOREWARD

Dr. Michael Naughton

This is the 30th year of the Bureau of Meteorology's annual research and development workshop. During this time, there has been a shift from focussing on deterministic forecasting methods and communication to explicitly including probabilistic information. One of the key methodologies in making this change has been to use an ensemble of forecasts rather than a single model realisation.

The physical modelling of environmental systems has been so successful over the past few decades that it is a critical element of modern society. The predictions and outlooks from environmental modelling systems have a major impact on society, supporting activities such as emergency services, energy, major primary industries, transport, long term risk evaluation and planning, down to every day personal decisions. The three pillars of this success have been advances in modelling science, observing technology and computing power.

Prediction uncertainty is an intrinsic characteristic of complex physical systems such as the atmosphere and ocean, and additional uncertainty is added by limits on the observations and on model physics and resolution. The approach that we are focusing on in this workshop is the use of ensemble methods to model uncertainty. Ensemble methods are employed in a wide range of different ways, from the fundamental mathematical formulation to combination of forecasts or projections from different sources.

Ensemble approaches have contributed to producing more accurate and informative products, but they have also brought challenges in how to handle the increased data volumes that they produce, and how to condense and communicate information effectively.

This workshop brings together a large and diverse group of researchers from universities, operational centres and other research organisations to look at ensemble methods across a range of timescales from nowcasting for the next few hours to climate change projections on multi-decadal timescales. A key component of the workshop will be to consider how ensembles deliver the best value to the Bureau's forecasting activities and climate applications.

The workshop is organised around six session themes

- Ensemble methods for weather prediction modelling
- Ensemble weather forecasting applications
- Bureau national forecast services and business sectors
- Ocean and storm surge modelling
- Seasonal prediction
- Climate and water projections

We are pleased to welcome the prominent scientists and experts from overseas, Australian research agencies and universities who have been invited to give presentations. Keynote speakers include

- TimPalmer, Oxford University
- Roberto Buizza, Scuola Superiore Sant'Anna, Pisa & ECMWF
- Warren Tennant, UK Met Office
- Ilene Carpenter, CRAY
- Aurore Porson, UK Met Office
- Craig Bishop, University of Melbourne
- Gary Weymouth, BoM
- Jonathan Flowerdew, UK Met Office
- Oyvind Breivik, Norwegian Met Institute
- Pat Hogan, US Naval Research Laboratory
- Magdalena Balmaseda, ECMWF
- Reto Knutti, ETH Zurich
- Gab Abramowitz, University of NSW
- Berit Arheimer, Swedish Met and Hydrological Institute

The workshop is hosted by the Bureau of Meteorology (BoM). The workshop is sponsored by BoM, Cray, Altair and National Computational Infrastructure (NCI). Cray is acknowledged as the workshop's Gold Sponsor. I would like to thank these sponsors for their generous support of the workshop.

As chair of the workshop organising committee, I sincerely thank the members of the organising committee: Saima Aijaz, Robin Bowen, Keith Day, Val Jemmeson, Sandra Marriott, Surendra Rauniyar, Grant Smith, Carlos Velasco, Griff Young, Meelis Zidikheri, as well as the scientific committee: Craig Bishop, Roberto Buizza, Beth Ebert, Tony Hirst, Simon McCulloch, Tim Pugh, Kamal Puri, Peter Steinle, Greg Stuart, Gary Weymouth.

Dr. Michael Naughton

Bureau of Meteorology

THE ECMWF ENSEMBLE PREDICTION SYSTEM: LOOKING BACK (MORE THAN) 25 YEARS AND PROJECTING FORWARD 25 YEARS

Tim Palmer

Atmospheric, Oceanic and Planetary Physics
University of Oxford

The origins of the ECMWF Ensemble Prediction System are outlined, including the development of the precursor real-time Met Office monthly ensemble forecast system. In particular, the reasons for the development of singular vectors and stochastic physics – particular features of the ECMWF Ensemble Prediction System - are discussed. The author speculates about the development and use of ensemble prediction in the next 25 years.

THE ECMWF ENSEMBLES OF ANALYSES AND FORECASTS

Dr Roberto Buizza

Scuola Superiore Sant'Anna (SSSA, Pisa, Italy)/European Centre for Medium-Range Weather Forecasts (ECMWF, Reading, UK)

ECMWF operational forecasts are generated using ensembles of analyses and forecasts. The former provides estimates of initial-time uncertainties to initialise the ensemble forecasts, and are used in data assimilation to estimate flow dependent background error statistics. Ensemble of forecasts provide users with estimate of forecasts uncertainties, expressed e.g. in the form of probability maps (of extreme values, tropical cyclone tracks, ..), cluster scenarios, extreme forecast indices. Some of these ensemble-based forecasts require ensembles of re-forecasts spanning the past decades to estimate the model climate, and calibrate the forecast probabilities. Furthermore, ensembles of coupled ocean/sea-ice/land/atmosphere reanalyses spanning the past 110 years have been generated to provide the distribution of the past climate, in terms of the most likely states and their confidence interval. In this talk, I will review the status ECMWF ensembles, and present on-going work to further improve them, as foreseen in the ECMWF 2016-2025 strategy.

MET OFFICE GLOBAL ENSEMBLE PREDICTION DEVELOPMENTS

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Introduction

The Met Office Global and Regional Ensemble Prediction System (MOGREPS) has been operational since 2008 (Bowler *et al.*, 2008). The current global model technical details are shown in Table 1. The global ensemble (MOGREPS-G) configuration has generally favoured spending more of the compute resource on resolution than ensemble size, but we boost the latter by lagging the two most recent forecast cycles to form a combined ensemble size of 36 members every six hours. All post-processing is driven this way.

Initial condition perturbations

Initial condition perturbations are generated by the Ensemble Transform Kalman Filter (ETKF) scheme (Bishop *et al*, 2001). This uses a 6-hour background forecast from each ensemble member and observations valid during this assimilation window to produce initial perturbations for the next cycle. This is done using a transform matrix and inflation scheme such that the ensemble spread matches the 6-hour forecast error of the ensemble mean in each of 92 equal-sized regions around the globe. A vertically-varying inflation scheme applied over four layers ensures a more realistic vertical distribution of spread.

MOGREPS-G has used the ETKF scheme since it became operational, but this will be replaced by an ensemble of 4D-ensemble-Var (En-4DEnVar) scheme (Bowler *et al.*, 2017) during 2019. The main advantage of En-4DEnVar is that it uses existing code within the deterministic 4D-Var data assimilation system (Clayton *et al.*, 2013), including sophisticated model-based localisation. This also aligns the deterministic data assimilation background error covariances more with the ensemble.

Table 1: Technical details of the Met Office operational global deterministic and ensemble modelling systems in 2018. Red text denotes changes that went operational in OS41 during September 2018.

	Deterministic	Ensemble (MOGREPS-G)
Resolution (grid points)	2560x1920 regular lat/lon ~10km in mid-latitudes	1280x960 regular lat/lon ~20km in mid-latitudes
Vertical levels & Time-step	70 levels (model top 80 km) Time-step = 4min	70 levels (model top 80 km) Time-step = 7.5min

Science configuration	Atmosphere: GA6.1 – Walters *et al* (2017a) Land: GL8.1 – Walters *et al.* (2017b)	Atmosphere: GA6.1 – Walters *et al* (2017a) Land: GL8.1 – Walters *et al.* (2017b)
Forecast length & frequency	7-days at 00Z and 12Z 2.5-days at 06Z and 18Z	17 pert + 1 control = 18 members to 7-days every 6 hours. Lag two cycles = 36-mem
Initial conditions	hybrid-4D-Var	Interpolated from high-resolution deterministic analysis
Initial condition perturbations	none	Ensemble Transform Kalman Filter (using 44 members)
Stochastic physics	none	SKEB + Stochastic Perturbation of Tendencies (SPT) (Sanchez *et al.*, 2016)
Surface perturbations	none	SST, soil-moisture and deep soil-temperature (Tennant and Beare, 2014)

Stochastic physics perturbations

MOGREPS-G has utilised a number of stochastic physics schemes to address model uncertainty. The factors that have played a role in choosing these include physical realism or justification (e.g. a missing physical process in the model), ease of implementation and ongoing maintenance, compute resource cost, and effectiveness in controlling ensemble spread.

Random Parameters (RP2)

The first scheme used in MOGREPS-G was a form of perturbed parameters, where a selection of physics parametrization scheme parameter settings are perturbed globally within a prescribed range, using a random AR1 process to evolve these values over time. This scheme did a reasonable job at increasing the spread in screen temperature and precipitation, but generally only had a modest impact on increasing large-scale ensemble spread and also involves a large overhead to maintain relevant parameters and sensible perturbation ranges. For these reasons, it was retired in Operational Suite 41 (OS41) that went live in September 2018.

Stochastic Kinetic Energy Backscatter (SKEB)

The primary stochastic physics scheme in MOGREPS-G for many years has been the SKEB scheme (Tennant *et al.*, 2011). This uses diagnosed 3D fields of energy loss, from missing physical processes in the forecast model convection scheme and smoothing from the semi-Lagrangian advection scheme, to modulate an evolving random pattern with a prescribed power-spectrum. This produces wind-increments at each forecast time-step. The scheme was upgraded at OS41 to improve the features of the random pattern in high-latitudes and to make the scheme more scale-aware (Sanchez *et al.*, 2016).

Stochastic Perturbation of Tendencies (SPT)

SPT, more generally known as Stochastically Perturbed Physics Tendencies (SPPT, Buizza et al., 1999), perturbs the tendencies from selected physics parametrization schemes within a range, centred on zero, as forced by a 3D random pattern with prescribed horizontal length-scales. This pattern also evolves over time using an AR1 process. This scheme is simple and can be calibrated to provide the correct amount of spread in an ensemble. However, it has encountered stability issues in the Unified Model and a fair amount of work has been done to improve its stability and conservation of mass and energy properties, e.g. along sloping vertical coordinates (Sanchez *et al.*, 2016). SPT was implemented in MOGREPS-G at OS41.

Analysis Increments (AI)

This scheme uses analysis increments from an archive of the operational 4D-Var data assimilation system, which are reconfigured to the ensemble resolution and applied at each model time step over a window of 6 hours for each ensemble member (Piccolo *et al.*, 2018). Every 6 hours a new random set of analysis increments is selected and applied to the forecast model. Preliminary experiments showed that the growth-rate of ensemble spread can be better controlled than before using this scheme (Fig. 1). The optimal impact is seen when using increments from the appropriate season, which could either be from a three-month lagged archive or from the same season from a previous year. While these increments do not represent the flow-dependent structures at the time of the forecast, they do retain the full geographical variation of the systematic errors of the forecast model, which may benefit both the reliability and the resolution of the ensemble.

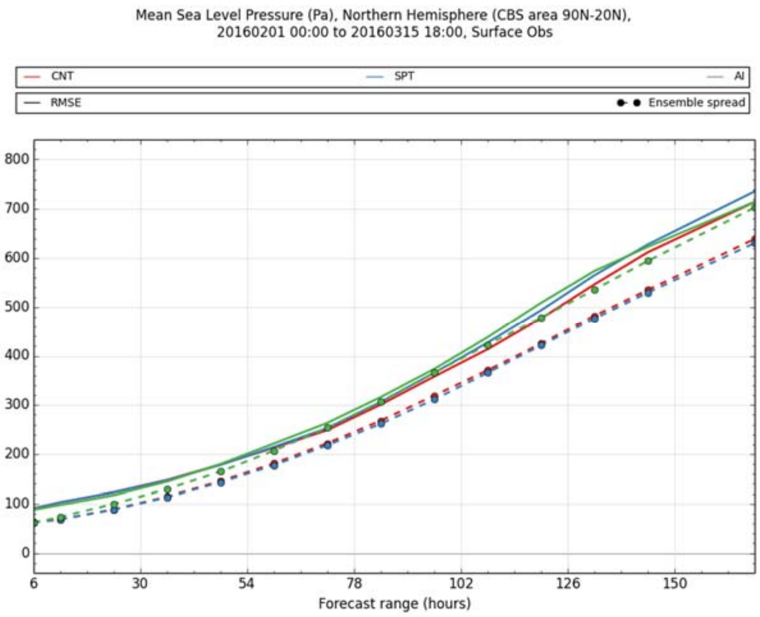

Figure 1: RMSE of the ensemble mean (solid) and ensemble spread (dashed) mean-sea level pressure forecasts by lead-time verified against Northern Hemisphere observations for operational ETKF MOGREPS-G control (red), SPT scheme (blue) and AI scheme (green).

Tropical cyclone forecasts

At the Met Office, tropical cyclone tracking is run in real-time on the MOGREPS-G, ECMWF EPS and NCEP GEFS ensembles. The three ensembles are also combined into a 108-member multi-model ensemble. A range of products, including track and intensity forecasts for both named and forming storms, are produced and distributed to several operational tropical cyclone forecasting centres. The probabilistic forecasts from each global ensemble, and the various multi-model combinations, are evaluated using a probabilistic verification framework. Generally, the three systems are comparable, with no single system showing the best score in all ocean basins (Fig. 2). However, a combined multi-model ensemble has the highest score throughout, clearly showing the benefit of data exchange to help improve guidance for high-impact weather events such as these.

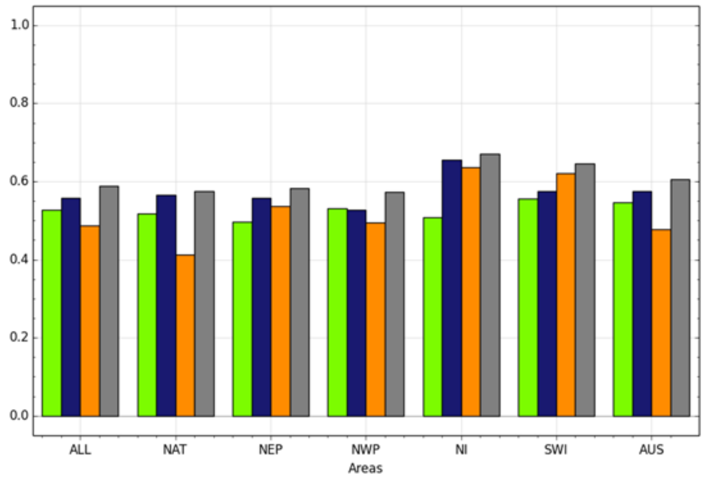

Figure 2: Brier Skill Score of MOGREPS-G (green), ECMWF EPS (blue), NCEP GEFS (orange) and multi-model ensemble forecasts (grey) of strike probability for all named storms in the period July 2017 to June 2018. These are split by tropical cyclone basin – North Atlantic (NAT), northeast Pacific (NEP), north Indian (NI), southwest Indian (SWI) and Oceana (AUS).

Summary and future work

MOGREPS-G ranks among the top-performing global ensemble prediction systems. Recent upgrades to the stochastic physics and the upcoming move to En-4DEnVar is expected to make significant improvements to the ensemble skill and reliability. It is acknowledged that MOGREPS-G is somewhat under-dispersive for some forecast fields, something which should be reduced with upcoming upgrades. We are also investigating options to target the spread around tropical cyclones through the use of targeted perturbed observations in those locations.

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BOM ACCESS-GE GLOBAL ENSEMBLE NUMERICAL WEATHER PREDICTION SYSTEMS

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BoM has been developing and running ensemble numerical weather prediction systems in research mode since the second half of the 1990's, originally based on the Australian global and regional NWP systems, and then on ACCESS versions of the UK Met Office MOGREPS systems. Up until now, these EPS systems have been run in research demonstration and operational trial versions. ACCESS NWP systems are scheduled to become operational in the first half of 2019.

The first Bureau global EPS (GASP-EPS) was developed for the Bureau's GASP global spectral model using the singular vector initial conditions perturbation method developed at ECMWF. It was run quasi-operationally in the Bureau's operational suite from 2002 to 2009.

An Australian region EPS (LAPS-EPS) was developed and run from 2002-2005, based on the Bureau's Australian region LAPS system, which included both perturbed initial conditions and perturbed physics.

From 2006 onwards, BoM, CSIRO and Australian universities started the Australian community climate and earth systems simulator (ACCESS) national partnership. ACCESS NWP systems are predominantly based on the corresponding UK Met Office Unified Model (UM) systems. The global ACCESS-G system became operational in 2009.

The ACCESS-GE global EPS system was developed from 2007 onwards, based on the MOGREPS-G system. ACCESS-GE has been running routinely in near-real-time since around 2010.

Skill performance of both the GASP-EPS and ACCESS-GE EPS systems has been comparable to operational EPS systems in other major world meteorological centres.

The current ACCESS-GE2 60 km resolution version has been running routinely since 2014 as a demonstration system. ACCESS-GE2 has been used by several groups to develop downstream ensemble products.

The ACCESS-GE3 version currently running in pre-operational trials is planned to become operational in 1Q 2019. It is based on the 2017 Met Office PS39 system, at 33 km resolution.

ACCESS-GE3 skill improves upon ACCESS-GE2, in line with forecast skill improvement of ACCESS-G3 relative to ACCESS-G2.

There are a number of major differences in the upgrade from APS2 to APS3, which all contribute to the forecast improvement:

EPS: increased number of ensemble members, additional forecast model perturbations;

Model: increased resolution, change from new dynamics to ENDGame UM dynamical core;

Data assimilation: hybrid ensemble 4D-VAR, upgraded background error covariances and introduction of new observations sources.

IMPLEMENTATION AND PRELIMINARY RESULTS OF HIGH RESOLUTION ENSEMBLE PREDICTION SYSTEM AT NCMRWF

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National Centre for Medium range Weather Forecasting (NCMRWF), India has been running global ensemble prediction system (NEPS) based on Met Office Global and Regional Ensemble Prediction System (MOGREPS-G) since October, 2015. This ensemble system has been updated recently and the updated version was made operational on 1 June, 2018. Previous version of NEPS had horizontal resolution of 33 km and ensemble size of 45 (44 perturbed + 1 control) members. The horizontal resolution of the current operational NEPS has been increased to 12 km. The initial condition perturbations of this ensemble prediction system are generated by Ensemble Transform Kalman Filter (ETKF) method (Bowler et al., 2009) and model uncertainties are taken care by the Stochastic Kinetic Energy Backscatter and Random Parameters schemes (Tennant et al., 2011). The forecast perturbations obtained from 6 hour short forecast run of 22 ensemble members are updated by ETKF four times a day (00, 06, 12 and 18 UTC). Perturbations of surface parameters such as sea-surface temperature, soil moisture content and soil temperature (Tennant and Beare, 2014) are included in the 12-km NEPS in order to address the problem of lack of ensemble spread near the surface. The NEPS aims to provide 10-day probabilistic forecasts using 23 members (22 perturbed + 1 control) ensemble system. Out of 22 perturbed ensemble members, one set of eleven members run from 00 UTC of current day and the other set of 11 members run from 12 UTC of previous day to provide ensemble forecast of 10 days. The operational deterministic forecast running at 12 km resolution from 00 UTC is used as the control forecast.

As 12 km NEPS is implemented first time in NCMRWF, initial condition perturbations were not available at this resolution. Therefore, ensemble members with perturbed model physics were cold-started from the same initial condition (analysis of deterministic model). The results of experiments indicate that the spread of the cold started ensemble members becomes nearly equal to the operational NEPS ensemble spread after 15-16 short forecast cycles. Figure 1 shows that spread in specific humidity at 5600 m height of 17km NEPS takes about 16 short forecast cycles to become nearly equal to that of the operational 33 km NEPS. A technical report by Mamgain et al., 2018 describes in detail the operational implementation of this high resolution EPS at NCMRWF.

Both the 33 km and 12 km NEPS were operational during 1st June 2018 to 16th July 2018. A comparative study has been carried out to investigate the improvement in model performance due to the change in NEPS configuration based on the forecasts by both the systems during this period. The study has been conducted for both the hemispheres of the globe as well as for the tropical region separately. The relationship between root mean square error and ensemble spread with forecast lead time has been compared for both the systems. The verification of probabilistic forecasts from both the systems is carried out by testing the reliability, consistency and accuracy of the prediction system. The ability of the NEPS to discriminate the situations leading to occurrence and non occurrence of events has also been investigated.

The performance of 12 km NEPS has also been analyzed for heavy rainfall cases over Indian region.

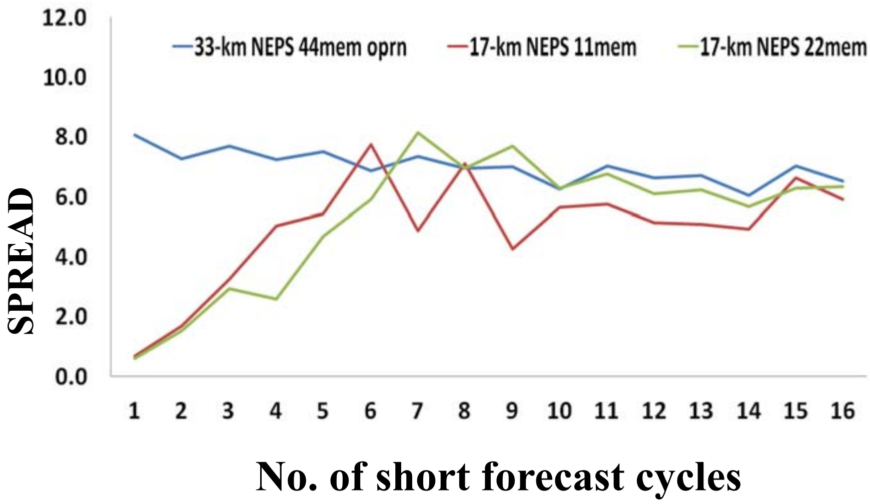

Fig 1: Ensemble spread in Specific Humidity at 5600m height

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HIGH RESOLUTION (12.5 KM) ENSEMBLE PREDICTION SYSTEM BASED ON GEFS: EVALUATION OF EXTREME PRECIPITATION EVENTS OVER INDIAN REGION

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Introduction

State of the art, atmospheal circulation model (AGCM) National Center for Environmental Prediction (NCEP) Global Forecast System (GFS) at horizontal resolution of T1534 (~12.5 km) with 64 vertical levels have been established at Indian Institute of Tropical Meteorology, Pune, India in its deterministic form and also in ensemble prediction system (EPS) with 21 members. The deterministic system is made operational in India Meteorological Department (IMD) since 2016 and the EPS system has been made operational since 1 June 2018. The GEFS and GFS prediction system was the need of the hour particularly in the backdrop of increasing extreme rain events over the sub-continent as reported by several recent studies (Roxy et al. 2017; Goswami et al. 2006; Rajeevan et al. 2008). The 12 km EPS system based on GEFS has been applied for a variety of sectors namely block level (experimental) precipitation probability forecast, forest fire monitoring and forecast, wind and solar energy forecast and most importantly for extreme rain forecasts. Her we are providing some glimses of performance of the GEFS and GFS forecasting system for recent heavy rainfall episodes over Indian region.

Data and Methodology

The GFS model dynamical core is based on a two time-level semi-implicit semi-Lagrangian (SL) discretization approach (Sela 2010), while the physics is done in the linear, reduced Gaussian grid in the horizontal space. It is the first time that the SL dynamical core (previously Eulerian (EL)) is implemented in GFS T1534 for operational forecast over India equivalent to other global operational centers namely ARPEGE (Meteo France), GEM (Environment Canada), GFS (NCEP), GSM (JMA), IFS (ECMWF), MetUM (UKMO) etc. The major advantage of SL framework over EL approach is that it is an unconditionally stable scheme which shows very good phase speeds and sufficient accuracy. It also saves lot of computational time as compared to EL framework due to longer time steps. A detailed description of the benefits of SL approach is described in detail in the study by Staniforth and Cote (1991). Figures 1 and 2 respectively describe the schematic of GFS T1534 and GEFS T1534 system. The initial conditions (ICs) for the forecast are generated by NCMRWF through the Global Data Assimilation System (GDAS) cycle which has more Indian data into it. More details about the NCMRWF data assimilation system is documented in Prasad et al. (2016). For the GEFS run, the perturbed ICs are being generated at NCMRWF and passed on to IITM for subsequent forecast run.

Results and Discussion

A recent episode of extremely heavy rainfall during August 2018 over the southern Indian state Kerala has been predicted with 2 to 3 days lead time. The rainfall over Kerala during 1-19 August was 164% more than normal. The GEFS was able to show a reasonable probability with 5 to 7 days lead for a threshold of climatology and 1 standard deviation. Apart from these heavy rain episodes, these two modelling systems are efficiently predicting the rainfall probability and rainfall intensity associated with the monsoon depression and also with the tropical cyclones as see in the recent twin cyclones "TITLI" and "LUBAN" over the Bay of Bengal and Arabian sea respectively. These modelling systems are working as the main workhorse for the current weather forecasting in India. Efforts are on to improve the physical parameterization and also the dynamical core of the modelling systems to make it even more efficient in predicting the extremes.

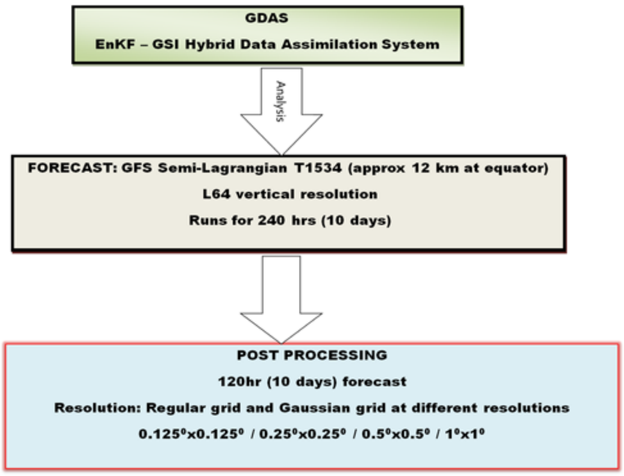

Figure 1. Schematic of GFS T1534

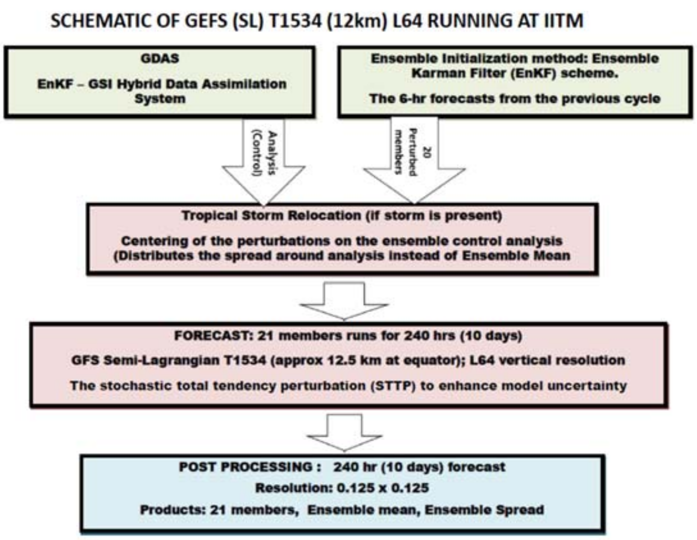

Figure 2. Schematic of GEFS T1534

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IDEAS FOR ENSEMBLE TROPICAL CYCLONE PREDICTION

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Tropical cyclones (TCs) are high impact weather events for which uncertainty information for both track and intensity can be critically important for emergency management decision-making. Even the best deterministic Numerical Weather Prediction models are prone to some degree of forecast error arising from both uncertainty in the initial analysis and growth of model error. The pragmatic forecasting approach is to utilise a range of track and intensity forecasts from a variety of sources, including the local and overseas deterministic forecast models, as well as overseas ensemble products.

The resulting track forecasts are generally reasonable but cyclone intensity can be more difficult to forecast. The Bureau of Meteorology has an operational bias correction system which substantially improves the intensity and R34 wind radii predictions from global NWP models which are then used as input to the JIP-TC ensemble wave model. The bias corrections improve the ocean response, duration of gales, and width of damage swath. The bias correction system also provides a range of intensities, which is seen as a critical information for user decision making. However, in the longer term, a preferable solution is an ensemble of higher resolution models which are necessary to resolve the scales needed to capture both the intensities and the rapid change in intensity often found in real tropical cyclones.

The Bureau currently runs two high-resolution TC-specific deterministic Numerical Weather Prediction systems: ACCESS-TC (12km resolution, 3-day forecasts for up to 3 concurrent TCs on relocatable 33°x33° domains within the Greater Asian tropics covering the Western Pacific and Eastern Indian Oceans); and ACCESS-TCX (4km resolution, 5-day forecasts on a fixed 25°x40° domain over the NW coast of Australia). At present though, the Bureau does not run any operational ensemble NWP systems of its own. This talk will discuss the pros and cons of some approaches for ensemble tropical cyclone NWP within the Bureau.

CRAY'S VISION OF DATA-CENTRIC COMPUTING FOR METEOROLOGY

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As the volume of data, both from observations and from model output, increases, weather centers are likely to become much more focused on the ability of HPC systems to handle and use data efficiently and somewhat less focused on things like how many ranks a single high-resolution model can scale to. The ability to quickly analyze the output from ensemble forecast systems, to apply AI techniques to identify severe weather features in model output and satellite imagery and to improve forecast accuracy through improved data assimilation methods all require attention to the storage on HPC systems. Data analytics and AI techniques have become part of the toolkit and will be used in a variety of ways to complement traditional numerical methods, but the I/O patterns they generate differ substantially from our traditional workloads.

Concurrent with this broadening in workloads, the storage hierarchy on HPC systems will continue to get deeper, with non-volatile memory joining flash-based SSDs and high capacity HDDs. How can NVM technology be used to accelerate data-intensive meteorology work? Where should flash based storage go and how should it be used? How do we know what we need and how can we manage it when we have it?

This talk will present Cray's vision for a flexible, data-centric architecture that brings data to compute resources in new ways to enable productive supercomputing in meteorology.

HOURLY CYCLING AND TIME-LAGGING: A NEW CONFIGURATION FOR MOGREPS-UK

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Abstract

At the UK Met Office, we have developed a new convective-scale ensemble configuration, based on hourly re-centring on the high-resolution deterministic model. The new hourly configuration runs a subset of 3 members, every hour, centred on a new 4DVar analysis. The boundary conditions are provided by our global ensemble model, MOGREPS-G, and are updated every 6 hours. The new configuration aims at improving the timeliness of the operational forecasts as well as improving the spread of the ensemble by using different analyses. The resulting ensemble is then time-lagged over 6 subsets to create an 18-member ensemble at 2.2 km grid spacing.

This new configuration is trialled in our parallel suites. Compared to the current 6-hourly configuration (in which all members are updated every 6 hours), the first verification scores show promising results in the short-range for most variables, except for the temperature field, where errors seem to be more dependent on the recent analysis.

The new hourly configuration is also trialled to run to T+120 instead of the current T+54. A new assessment baseline has been tested to validate the model beyond the current T+54. This new assessment includes a comparison against our deterministic high-resolution model as well as against our global ensemble model. It is based on objective verification and subjective evaluation from the operational meteorologists.

In this presentation, we will summarize the latest results of our trials regarding this new configuration.

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ACCESS-CE3 – THE BUREAU'S CONVECTIVE SCALE NWP ENSEMBLE

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Introduction

The Australian Bureau of Meteorology (Bureau) is currently developing and implementing its first convective scale ensemble forecasting system. Numerical Weather Prediction (NWP) ensembles are designed to sample the possible future state of the atmosphere by acknowledging and attempting to account for sources of uncertainty in weather forecasting. High-resolution NWP ensembles are able to provide information on high impact weather events, and their uncertainties, on the time-scales of a few days.

The Australian Community Climate and Earth-System Simulator (ACCESS) City Ensemble (ACCESS-CE3 or CE3) is currently under active development and has recently begun full scale trials. This system leverages information from the third generation Australian Parallel Suite (APS3) Global Ensemble (ACCESS-GE3 or GE3) and the City deterministic system (ACCESS-C3 or C3) to generate a 0.0198° (~ 2.2 km), 18 member ensemble over six city domains as shown in Figure 1.

ACCESS-CE3

ACCESS-CE3 is a convection permitting model (Clarke et al., 2016) based on the Parallel Suite 39 (PS39) Met Office Global and Regional Ensemble Prediction System (MOGREPS) high-resolution ensemble system, MOGREPS-UK (Tennant and Beare, 2014; Tennant 2015; Hagelin et al., 2017). CE3 is a 2.2 km grid-spaced system with 18 members, cycling four times a day over the six city domains, Figure 1. The blue dashed lines represent the location of the (second generation) APS2 city domains while the black lines represent the uniform core of the APS3 city domains (a slight offset has been applied to the APS2 Perth and VicTas domains for visualisation purposes; the APS2 and APS3 domains are exactly the same). All APS2 domains are fully encapsulated by the APS3 domains except the Darwin domain. This domain has been shifted to avoid the variable grid system (discussed below), extending the full Darwin domain (green lines in Figure 1) into the high elevation areas of Papua New Guinea.

The variable resolution grid spacing is 0.036° (~ 4 km) from the boundaries (green lines in Figure 1) to the transition zone (red lines in Figure 1), approximately 40 grid cells into the domain. Grid spacing is reduced in the transition zone from 4 km to 2.2 km over approximately 22 grid cells, forming the inner uniform core of the domain (black lines). The variable resolution grid allows direct nesting of the Local Area Model (LAM) within a coarse grid driving model by reducing the resolution mismatches at the boundaries, eliminating the requirement of intermediate grid length model runs (Tang et al., 2013).

The base initial conditions for CE3 are provided by C3, a 1.5 km resolution system with a 4D-Var Data Assimilation (DA) cycle. Large scale perturbations and lateral boundary conditions are provided by GE3. The large scale perturbations, the residuals from the global ensemble members and control member, are integrated with the base initial conditions to create unique initial conditions for each CE3 ensemble member. The majority of the spread in the ensemble is due to the initial condition perturbations and boundary conditions. The remaining spread is generated by the stochastic physics package known as the Random Parameter (RP) scheme.

The RP scheme aims to incorporate uncertainty in the values of parameters in the model's physical parameterisation schemes. It varies the values of ten parameters within the model which cover the following physical processes: mixing in the boundary layer, cloud formation, cloud-top diffusion, precipitation and droplet settling near the surface (McCabe et al., 2016). The RP scheme's contribution to the overall spread of the ensemble is an order of magnitude less than the contribution from the large scale perturbations and boundary conditions, yet it is still important as it helps to address under-dispersiveness in the ensemble.

Summary and Future Plans

The Bureau's first convective permitting, 2.2 km grid-spacing NWP ensemble, ACCESS-CE3, is under active development. Full scale trials of an 18 member ensemble system capable of ingesting 4D-Var initial conditions from C3 have commenced. Early results from these trials will be presented.

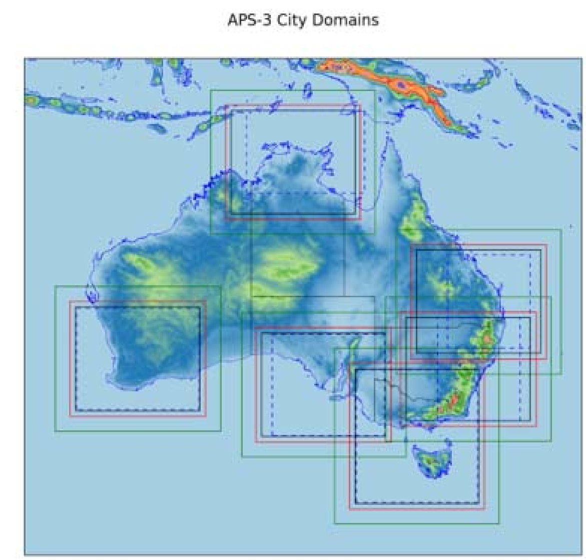

Figure 1: The location of the city domains. The dashed blue lines represent the APS2 domains. The green lines represent the outer boundary, the red lines represent the beginning of the transition zone and the solid black lines represent the uniform section of the APS3 domains.

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HIGH-RESOLUTION ENSEMBLE PREDICTION OF THE EAST COAST LOW OF APRIL 2015

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During autumn and winter months, the eastern coast of Australia is periodically affected by rapidly developing and intense extratropical low-pressure systems, commonly known as East Coast Lows (ECLs). ECLs bring damaging winds, heavy rainfall with flooding that can last for several days and coastal erosion. Due to their rapid development, many forecasting issues arise, such as predicting which part of the coast will be impacted, and the intensity and location of maximum winds and rainfall. The use of ensembles can help in overcoming these challenges, improve forecasts and better depict forecast uncertainty, and also give a better understanding of how these systems form.

The event studied here occurred during 20-23 April 2015, with the most severe impact on 21 April. It was the worst ECL event in nearly a decade and a devastating event for the Dungog and Maitland area (about 200 km north of Sydney), with at least four deaths reported and widespread damage. This event was simulated using a 24-member ensemble of the Australian Community Climate and Earth-System Simulator (ACCESS) nested models (global, 4.0 km and 1.3 km). The smallest grid spacing (1.3 km) sufficed to capture the dynamics of the event. The simulated ensemble-mean forecast rainfall is in good agreement with observed rainfall and the ensemble identifies Dungog as the area at significant risk of extreme rainfall.

Here, ensemble sensitivity is investigated, to understand how different dynamic features of the flow are related to the predictability of the event. A subset of ensemble members shows very little rain around the Dungog area; in these ensemble members the heaviest rain was moved further south or east, indicating that a large part of the coast was at risk of significant rain.

USING OBSERVATIONS TO IMPROVE ENSEMBLE-BASED CLIMATE PROJECTIONS AND THE ENSEMBLE DEPENDENCE TRANSFORMATION

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Abstract

We introduce the "replicate Earth" ensemble interpretation framework, based on theoretically derived statistical relationships between ensembles of perfect models (replicate Earths) and observations. We transform an ensemble of (imperfect) climate projections into an ensemble whose mean and variance have the same statistical relationship to observations as an ensemble of replicate Earths. We use a 'perfect model' approach to test whether this Ensemble Dependence Transformation (EDT) approach can improve 21st century CMIP projections. In these tests, where 21st century model simulations are used as out-of-sample 'observations', the mean square difference between the transformed ensemble mean and 'observations' is on average 30% less than for the untransformed ensemble mean. In addition, the variance of the transformed ensemble matches the variance of the ensemble mean about the 'observations' much better than in the untransformed ensemble. Results show that the EDT has a significant effect on 21st century projections of both surface air temperature and precipitation. It changes projected global average temperature increases by as much as 16% (0.2C for B1), regional average temperatures by as much as 2.6C (RCP85) and regional average annual rainfall by as much as 410mm (RCP60). In some regions, however, the effect is minimal.

HYBRID ENSEMBLE VAR FOR A LIMITED AREA MODEL

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Motivation

Data assimilation aims at providing an optimal state of the atmosphere by weighting contribution from prior knowledge about the state of the atmosphere and from observations. Prior knowledge is usually represented by a past forecast valid at the time of optimisation and its contribution to the optimised state of the atmosphere is weighted by an error covariance matrix, commonly called a background error covariance matrix in the context of variational data assimilation. Grid point-wise specification of the covariances in this matrix is not tractable, let alone due to storage requirements it would entail. Traditionally, therefore, in variational data assimilation, these statistics have been modelled (Lorenc et al., 2000) outside of a cycling numerical weather prediction (NWP) system. The parameters intervening in covariance modelling are estimated using samples of atmospheric states as produced by NWP simulations over selected past periods and transferred to a cycling system where they remain static over long periods of time. The covariance model constructed in this way accounts for climatological features of the flow and, in addition, its model is based on strong hypotheses of isotropy and homogeneity. While the covariance modelling approach made the problem of using high-dimensional matrices of error statistics tractable, in presence of strong gradients this approach leads to sub-optimal estimates of the state of the atmosphere. At present, ever finer improvements to the numerical forecasting are sought rendering the climatological formulation of the background error statistics insufficient. Hence, the rest of this abstract focuses on how to remedy this problem with a contribution of an ensemble prediction system (EPS).

Hybrid ensemble 4D-Var

In parallel to the approach of modelling of the background error covariance matrix for variational data assimilation, in the realm of ensemble methods developed around Kalman filtering, reduced rank covariance matrices which are based directly on members of the EPS are employed. Contemporary NWP cycling systems reflect spatial and temporal variations in the observation network via the construction of an atmospheric analysis and they subsequently propagate error structures using the full nonlinear model in an EPS forecast step. Hence, the error covariance matrix $\mathbf{B_e}$ based on the EPS reflects the present state of the atmosphere and accounts for flow dependencies. Consequently, a remedy to the problem of a lack of representation of the errors of the day in variational data assimilation could be to replace the climatological background error covariance matrix, $\mathbf{B_c}$ with $\mathbf{B_e}$. One striking characteristic of the error covariance matrix derived from the EPS is that it is rank deficient, having at most the rank equal to the ensemble size. Another problem which it brings alongside resides in spurious correlations appearing due to a limited size of the sample, which is counterintuitive as the errors at distant regions should be uncorrelated resulting in a larger number of independent structures than those described by a raw

$\mathbf{B_c}$. Hence, an idea of a hybrid method emerged (Hamill and Snyder, 2000) which advocates forming a linear combination of two covariances

$$\boldsymbol{B} = \beta_c^2 \boldsymbol{B_c} + \beta_e^2 \boldsymbol{B_e}$$

so that qualities of one will be complemented with the qualities of the other. However, even the hybrid approach requires additional treatment of the ensemble covariances commonly encountered in Kalman filtering, namely localisation.

Variational data assimilation optimizes the state of the atmosphere by minimizing a cost function and its practical implementation requires preconditioning of the problem so that the quadratic term in the cost function is represented by a unit matrix. A sequence of three transforms was therefore devised to remove inter- and intra-variable correlations in model variables so that they could be replaced with uncorrelated control variables of unit variance. First, a parameter transform, $\mathbf{T_p}$, transfers model variables to the space of control variables, which are further decorrelated via geometrical transforms, a vertical one, $\mathbf{T_v}$, projecting onto a set of uncorrelated empirical vertical modes and a horizontal one, $\mathbf{T_h}$, projecting, in case of a limited area model, on Fourier modes. Consequently, following (Clayton et al., 2003), the analysis increment in model space, $\delta\mathbf{w}$, is mapped to a control variable, $\mathbf{v}$, using a sequence of these three transforms

$$\boldsymbol{T}\delta\boldsymbol{w} = \boldsymbol{T_h}\boldsymbol{T_v}\boldsymbol{T_p}\delta\boldsymbol{w} = \boldsymbol{v},$$

while the (approximate) inverses of the aforementioned operators, $\mathbf{U_p}$, $\mathbf{U_v}$ and $\mathbf{U_h}$, respectively, are used to define an inverse transform, mapping the control variable $\mathbf{v}$ to the model increment $\delta\mathbf{w}$,

$$\delta\boldsymbol{w} = \boldsymbol{U}\boldsymbol{v} = \boldsymbol{U_p}\boldsymbol{U_v}\boldsymbol{U_h}\boldsymbol{v}.$$

These transforms are directly related to the climatological background error covariance as they form its square root, $\mathbf{B_c}=\mathbf{U}\mathbf{U}^{\mathrm{T}} = \mathbf{U_p}\mathbf{U_v}\mathbf{U_h}\mathbf{U_h}^{\mathrm{T}}\mathbf{U_v}^{\mathrm{T}}\mathbf{U_p}^{\mathrm{T}}$. Similarly, a practical implementation of the ensemble covariance matrix, makes use of its readily available square root, $\mathbf{W}$,

$$\boldsymbol{W} = \frac{1}{\sqrt{K-1}}(\boldsymbol{w_1} - \overline{\boldsymbol{w}}, \boldsymbol{w_2} - \overline{\boldsymbol{w}}, \dots, \boldsymbol{w_K} - \overline{\boldsymbol{w}}) = (\boldsymbol{w'_1}, \boldsymbol{w'_2}, \dots, \boldsymbol{w'_K})$$

which is a rectangular matrix whose columns are formed by K scaled error modes $\mathbf{w_k}$'.Therefore, one can use $\mathbf{W}$ to transform model increment, $\delta\mathbf{w}$, into a control variable, in the ensemble context referred to as alpha control variable,

$$\delta\boldsymbol{w} = \sum_{k=1}^{K} \alpha_k \boldsymbol{w'_k}$$

where

$$\boldsymbol{v^{\alpha}} = (\alpha_1, \alpha_2, \dots, \alpha_K)^T$$

is such an alpha control variable. It is here that the localization of the error modes intervenes. Physically, it results in disconnecting spuriously connected error structures and, mathematically, in increasing the rank of the error covariance matrix. Technically, the localized background error covariance matrix, $\mathbf{B_e}$ is thus represented as $\mathbf{L}\circ\mathbf{WW}^{\mathbf{T}}$ where $\mathbf{L}$ is a localization matrix and $\circ$ represents a Schur, element by element, product of two matrices. The model increment can now be written as

$$\delta \boldsymbol{w} = \sum_{\boldsymbol{k}=\mathbf{1}}^{\boldsymbol{K}} \boldsymbol{\alpha_k} \circ \boldsymbol{w}'_{\boldsymbol{k}}$$

by generalizing scalars α_ks to fields of $\boldsymbol{\alpha}_{\mathbf{k}}$s. Also the localization matrix $\mathbf{L}$ needs to be factored in terms of its square root $\mathbf{U}^{\boldsymbol{\alpha}}$, $\mathbf{L}=\mathbf{U}^{\boldsymbol{\alpha}}\mathbf{U}^{\boldsymbol{\alpha}\mathbf{T}}$, which is subsequently split into horizontal and vertical transforms

$$\boldsymbol{U}^{\boldsymbol{\alpha}} = \boldsymbol{U}_{\boldsymbol{v}}^{\boldsymbol{\alpha}} \boldsymbol{U}_{\boldsymbol{h}}^{\boldsymbol{\alpha}}$$

so that the mapped alpha control variable is now $\mathbf{v}_{\mathbf{k}}^{\boldsymbol{\alpha}}$

$$\boldsymbol{\alpha_k} = \boldsymbol{U}^{\boldsymbol{\alpha}} \boldsymbol{v}_{\boldsymbol{k}}^{\boldsymbol{\alpha}}$$

and the full alpha control vector reads

$$\boldsymbol{v}^{\boldsymbol{\alpha}} = (\boldsymbol{v}_{\mathbf{1}}^{\boldsymbol{\alpha}}, \boldsymbol{v}_{\mathbf{2}}^{\boldsymbol{\alpha}}, \dots, \boldsymbol{v}_{\boldsymbol{K}}^{\boldsymbol{\alpha}})^T.$$

Implementing hybrid in this set-up (Clayton et al, 2013) results in an analysis increment of the form

$$\delta w = \beta_c \boldsymbol{U}\boldsymbol{v} + \beta_e \sum_{k=1}^{K} (\boldsymbol{U}^{\boldsymbol{\alpha}} \boldsymbol{v}_{\boldsymbol{k}}^{\boldsymbol{\alpha}}) \circ \boldsymbol{w}'_{\boldsymbol{k}}$$

where the extended (Lorenc, 2003) control variable vector $\mathbf{v}$ is now a concatenation of the climatological and alpha control variables

$$\tilde{v} = (\boldsymbol{v}, \boldsymbol{v}^{\boldsymbol{\alpha}})^T = (\boldsymbol{v}, \boldsymbol{v}_{\mathbf{1}}^{\boldsymbol{\alpha}}, \boldsymbol{v}_{\mathbf{2}}^{\boldsymbol{\alpha}}, \dots, \boldsymbol{v}_{\boldsymbol{K}}^{\boldsymbol{\alpha}})^T.$$

While localization constitutes a remedy to the problem of unphysical spurious correlations it also brings along a set of new challenges as it is affecting the dynamical structure of the error modes and hence requiring quite a subtle treatment. The hybrid method performs localization in the control space spanned by the stream function ψ, velocity potential χ, geostrophically-unbalanced pressure p^A and humidity μ. Localisation in model space allows not only to better account for non-local observations and but also renders increments which preserve geostrophic balance to a larger extent than it would be the case if localization was performed in the model space. A new form of the localized increment (Clayton et al, 2013)

$$\delta w = \boldsymbol{U_p}\left\{\beta_c \boldsymbol{U_v U_h v} + \beta_e \sum_{k=1}^{K} \boldsymbol{\alpha_k} \circ \left(\boldsymbol{T_p w'_k}\right)\right\}$$

exhibits the action of the parameter transform $\mathbf{T_p}$. This transform discards the balanced fraction of the pressure increment form the error mode $\mathbf{w_k}'$. Subsequently, the remaining unbalanced pressure is localized and after that the balanced fraction of the pressure increment is brought back to the analysis increment via the $\mathbf{U_p}$ transform. In this way the geostrophic portion of the analysis increment remains geostrophic even after localisation.

Localisation needs to be applied in both horizontal and vertical directions. In horizontal, a Gaussian form is implemented while vertical localization is more challenging for two reasons. Firstly, evidence was found that the correlation does not monotonically decrease with vertical distance (Ingleby, 2001). Secondly, it is not clear with respect to which vertical coordinate the correlation length scales could be constant across the levels. To circumvent these problems, vertical localization is performed in correlation space (Clayton et al, 2013) and is based on globally averaged values from $\mathbf{B_c}$ in such a way that if c_{avg} is the average correlation between two levels, the corresponding localized correlation is

$$c_{loc} = \left|c_{avg}\right|^{\frac{1}{R^2}},$$

where R is a parameter.

Implementation

The upcoming BoM global operational system, G3/GE3, will run a hybrid variational data assimilation as a default mode. The global system will be followed by a city system, referred to as C3/CE3. The latter, however, does not have the hybrid capability rendering the present coupling between the two systems one-way. In fact, C3 provides high resolution analysis to form a high resolution initial condition for the CE3 system. However, no feedback from the CE3 system to C3 is brought at present. A hybrid ensemble Var will ultimately constitute a system where such a feedback to C3 is provided and a CE3 ensemble would be used to build an ensemble-based contribution to the background error covariance which will be employed in variational data assimilation in a C3system, albeit both likely in a different version at that time.

At present, BoM is actively working on porting a hybrid capability for a limited area model as developed at the KMA (Korea Meteorological Administration) to BoM computing environment. This initial implementation will only loosely be connected to the C3/CE3 system, however, the operating environment and the system components are shared so that ultimately a two-way feedback system could be developed. To begin with, the hybrid system will run in an off-line mode using the ensemble members as precalculated by CE3. Still, an option for an on-line generation of the ensemble members will also be available. Both hourly 3D-Var and hourly 4D-Var will be supported.

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DOES THE MET OFFICE CONSORTIUM NEED TO DEVELOP AN ENSEMBLE FOR FORECASTING?

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Introduction

There are several reasons for running ensembles. One is to meet the needs of data assimilation which includes: providing background error covariance estimates; providing errors of the day estimates; and facilitating the use of data assimilation algorithms that circumvent the need for an explicit tangent linear model and its adjoint model (as required by 4d variational analysis). We will call these "data assimilation ensembles" (DAEs). Another is to provide improved forecasts by providing a range of possible outcomes with attached probabilities of occurrence. We will call these "forecast ensembles" (FEs). An important goal for an FE should be that it is able to make a good forecast even when the analysis has, by chance, an unusually large error. That is it should be more reliable than a deterministic forecast. At the very least it should be able to recognise when an unusually large analysis error may have occurred and that the forecast is unusually unreliable.

Current Met Office Ensembles

The Met Office currently runs an 18 member global ensemble, MOGREPS-G, and an 18 member high resolution regional ensemble over the UK: MOGREPS-UK. The MOGREPS-UK members are initialised by reconfiguring the MOGREPS-G perturbations and recentring them on the deterministic high resolution UK analysis.

Although also used for ensemble forecasting, MOGREPS-G itself is primarily designed as a DAE (Bowler et al 2008; Bowler et al 2017). One consequence of this is that the ensemble uses what we shall call a "type I" sampling of the analysis error. That is the distribution of the initial state perturbations of the ensemble matches the distribution of errors around the analysis.

This makes sense in the context of a DAE: most of the ensemble members are sampling the most likely part of the error space allowing one to estimate it with more accuracy.

It is less clear, however, that this makes sense in the context of a forecast ensemble. From an FE point of view we appear to be over sampling small perturbations and under sampling larger ones. This has the effect of increasing the mean distance between the closest ensemble member and the true analysis as the analysis error in any particular instance increases.

This would appear to be in conflict with the desired goal of an FE to be able to make better than deterministic forecasts in those cases when the deterministic forecast has unusually large errors. The raises the question: can an FE do better?

What Might a Forecast Ensemble Look Like?

In order to meet our goal for an FE we need two things: to change the way the ensemble members sample the analysis error; and a way to estimate which part of the ensemble space truth is most likely to lie in which is more accurate than the analysis used to construct the ensemble.

Instead of the "type I" sampling used by the DA ensemble the FE could use a "type II" sampling. That is the ensemble members should sample the analysis error uniformly for sigma (number of standard deviations) less than a cut off value; and don't sample it all for sigma's greater than the cut off value. The cut off value is of course required because we can only run a finite number of ensemble members. Its value determines the frequency of events where truth lies outside of the ensemble. The uniform sampling for sigmas smaller than the cut off ensures a constant maximum distance between the true analysis and the nearest ensemble member. Together, the constant sampling density and the cut off sigma determine the number of ensemble members required. Of course a practical method has to be found to generate ensemble members with this type II sampling of the analysis error.

At the time of making an ensemble forecast (T_a) the analysis is the best available estimate of the true analysis. Hence the best estimate of the relative probability of each ensemble member being truth is equal to the probability of their initial perturbation given the analysis error distribution function (the absolute probability will also depend upon the sampling density and the cut off sigma). However, at some later time $T_{a+\delta}$ (with $T_{a+\delta} < T_{a+R}$ where T_{a+R} is the maximum forecast range the ensemble is run out to) we can use observations made during the interval $T_{a+\delta}$ to refine our estimate of the probability of each ensemble member being truth (and, if we wish, to estimate the value of the analysis error at time T_a). This refinement could be done using various (or indeed multiple) methods including: using an analysis made at $T_{a+\delta}$; a traditional regression algorithm using innovation vectors on the interval $T_{a+\delta}$ to predict the probability of a given ensemble member being truth at some later forecast range (up to T_{a+R}); or perhaps an appropriate machine learning algorithm to do the same which might benefit from having a representation of the nonlinear dynamics of the system. Regardless of the details of the refinement methodology the refinement process itself strongly suggests the formation of a lagged ensemble every member of which has an estimate of its probability of being truth. These, perhaps together with estimates of their accuracy (which might depend upon $T_{a+\delta}$) can be used in generating forecast products from the lagged ensemble.

Another interesting possibility is that one could also use this information to modify the background for the analysis at the current time and hence reduce the analysis error.

Including Other Sources of Forecast Error

So far we have only discussed sampling the analysis error. Whilst this is the largest source of forecast error it is not the only one. Other sources of initial state error include all the boundary values used to run the model such as sea surface temperatures and all the values supplied via ancillary files from orography to vegetation types. We can potentially include all of these by uniformly sampling the forecast error at some chosen forecast range perhaps using a method akin to singular vectors. The exact details of such a method to generate type II sampling of the forecast error are still to be worked out.

Model error, caused by approximations and errors in the model formulation, is another source of forecast error. This is usually sampled by running different ensemble members with different perturbations to their model formulations. It is not clear at present if this can be incorporated into the type II sampling methodology. If not one may have to resort to running multiple ensembles sampling model error each centred on one of the members of the ensemble sampling initial state error.

Conclusions

In this talk I shown that the method of sampling error/generating ensemble member initial states required for data assimilation ensembles is sub optimal for forecast ensembles.

I have outlined an alternative method for generating forecast ensembles, though many important details remain to be worked out, not least devising a method of generating ensemble members with a type II sampling of the forecast error.

At NIWA we are going to begin by investigating the efficacy of the forecast refinement approach outlined here.

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ON THE GENERATION OF STOCHASTIC SIMULATIONS OF RAINFALL IN SPACE AND TIME FOR HYDROLOGICAL APPLICATIONS

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Stochastic simulations of rainfall in space and time are required for modelling the impact of the spatial and temporal distribution of rainfall on the hydrological response of a catchment. Rainfall forecasts have significant uncertainty at the space and time scales of most catchments, and therefore large ensembles of rainfall forecasts are required as forcing for ensemble hydrological prediction systems.

The statistical properties of rainfall are strongly dependent on scale in both space and time, and this signature characteristic has important implications for hydrology. The Short Term Ensemble Prediction System (STEPS) uses a multiplicative cascade to model the spatial distribution of rainfall and a hierarchical second order auto-regressive model (AR2) to simulate the temporal evolution of rainfall in Lagrangian coordinates.

STEPS was developed to generate large ensembles of rainfall forecasts that are conditioned on observed and rainfall forecasts from Numerical Weather Prediction (NWP) models. The conceptual framework has also been used to generate ensembles of design storms, down-scaled climate model and low-resolution NWP rainfall fields, and blended radar, satellite, and NWP rainfall fields.

CONTINENTAL RAINFALL ENSEMBLE DERIVED FROM MULTI-SOURCE BLENDED ANALYSIS

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Introduction

Frequently-updated (i.e. <10 min latency) high-resolution quantitative rainfall estimates are key inputs to the accurate assessments of heavy rain associated with extreme weather and storms, and potential for flash-flooding. However, for a comprehensive, nation-wide rainfall analysis, there is no single source of rainfall data that possesses the desirable characteristics of coverage, resolution, accuracy and data latency for real-time applications. And while data accuracy and timeliness (i.e. low latency) are characteristics of utmost importance for real-time applications, the ability to reliably capture the spatial and temporal patterns of rainfall across a range of scales may be just as important for accurate catchment streamflow modelling and flood prediction.

The goal of producing high-resolution accurate estimates of rainfall on a national scale, within a few minutes of observation, is only likely to be achieved through the statistical blending of two or more rainfall data sources which may include rain gauges, radar, satellite, and numerical weather prediction model output (Fig.1). A real-time blended analysis is likely to gain wider use if it is accompanied by a spatially explicit representation of estimation accuracy, most usefully as a rainfall ensemble. In addition to providing a quantitative assessment of analysis uncertainty, an ensemble provides a means of computing probabilistic rainfall information, including of exceedance probability.

This presentation describes activities towards developing a national-scale real-time rainfall analysis service. We present our current plans to explore methods for blending multiple sources of (near) real-time rainfall data to generate rainfall analyses, including approaches underpinning MSWEP (Beck et al., 2016), STEPS (Seed et al., 2013) and a scale-dependent blending method (Renzullo et al., 2017). We focus discussion on our approach to ensemble generation based on perturbing rainfall analyses with structured noise following the STEPS method (briefly outlined below).

Method

Rainfall exhibits *scaling*, i.e. structure in spatial and temporal patterns across a wide range of scales. For gridded rainfall, scaling is evident in the data power spectral density (*PSD*) which follows a power law distribution,

$$PSD(\lambda) \propto \lambda^{\beta}, \qquad (1)$$

where λ denotes spatial dimension (*wavelength*, in km) and β is known as the spectral exponent, or spectral slope (linear PSD in log-log plot). While most rainfall data exhibit scaling, their representation of rainfall structure can vary across spatial scales (Fig. 2). The spectral slope is indicative of rainfall structure: high β suggest greater organization or smoothness; low β greater spatial irregularity or randomness. It is important that a blended analysis maintains scaling, with β in the range 2.2 – 3.0, to provide realistic patterns of rainfall distribution and structure across the widest range of spatial scales.

Our approach to ensemble generation, based on STEPS, is to perturb the gridded analysis with spatially structured noise. The structure is derived from the blended rainfall analysis, *via* mathematical convolution, thus ensuring that each ensemble member possesses the scaling properties of the blended analysis (Fig. 3). In addition, we will pay close attention to the error variances (or, indirectly, the magnitude) of the perturbations to ensure that the ensemble spread is indeed representative of the actual uncertainty in the blended analysis, and satisfy reliability criteria. Finally, we plan to extend the approach from local to national by concatenating series of spatially contiguous local analyses (Fig. 4), and providing a detailed evaluation of the ensembles through assessing the statistical reliability of the rainfall information products using independent rain gauge measurements.

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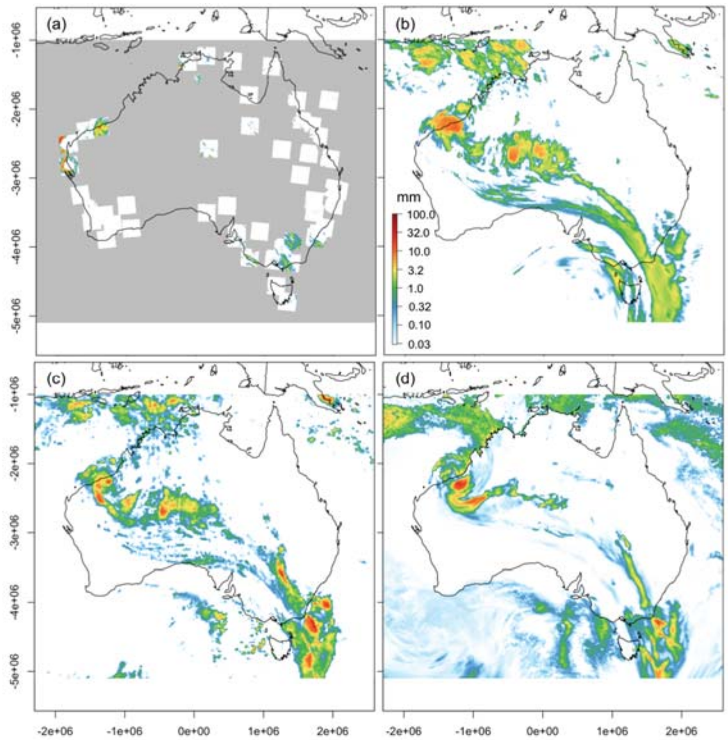

Figure 3. Accumulated rainfall (60-min) patterns across Australia for 15:00 hrs UTC on 12 Jan 2018 as captured by: (a) Rainfields v3.0; (b) Himawari-8 Convective Rain Rate Algorithm v1.0; (c) GPM IMERG 3B-HHR_L; and (d) ACCESS-R APS2 06Z forecast. Rainfall the remnants of cyclone Joyce.

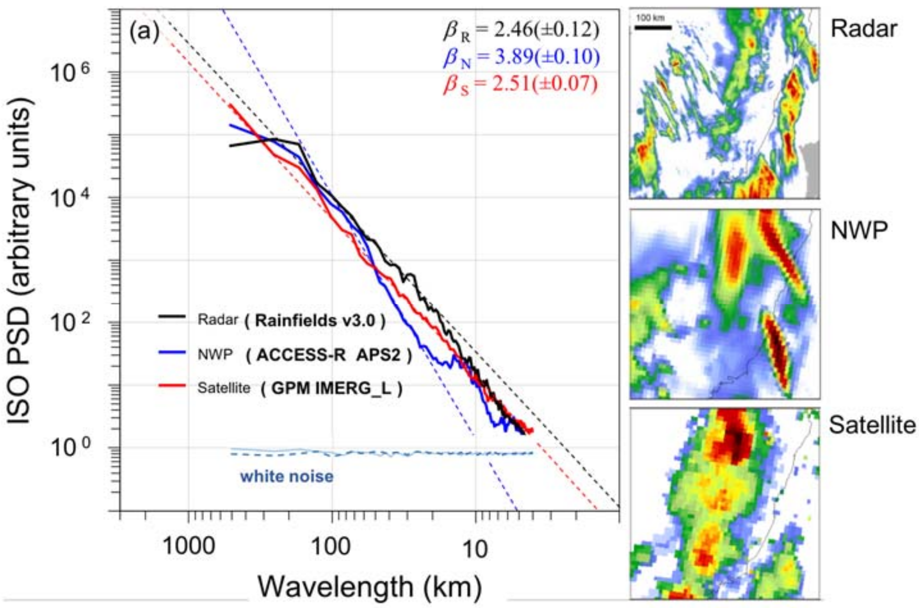

Figure 4. Isotropic power spectral density (ISO PSD) of the rainfall patterns in Rainfields (Radar), ACCESS-R (NWP) and GPM (Satellite) data shown on the left for NSW-Qld coast on 14:00 hrs UTC on 2 Sept 2016. The power law spectral slope, β, for the various sources, indicating the degree of organization of the data for given spatial scale: higher slopes more organization (smoothness); low slope less structure, PSD of white noise displayed for comparison.

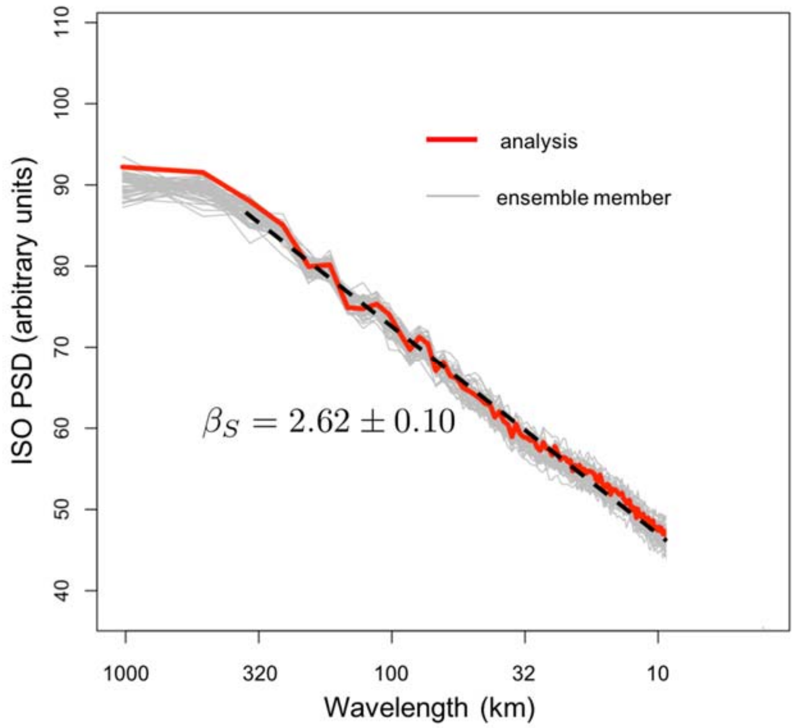

Figure 5. ISO PSD for 60-minute accumulated rainfall analysis (GPM in this case) over 1000 km x 1000 km Sydney region (red). Also displayed (in grey) ISO PSD for 50-member ensemble of rainfall derived from perturbing the analysis with structure noise. Average spectral slope for 20 – 100 km spatial scale is 2.62 with a standard deviation of 0.1.

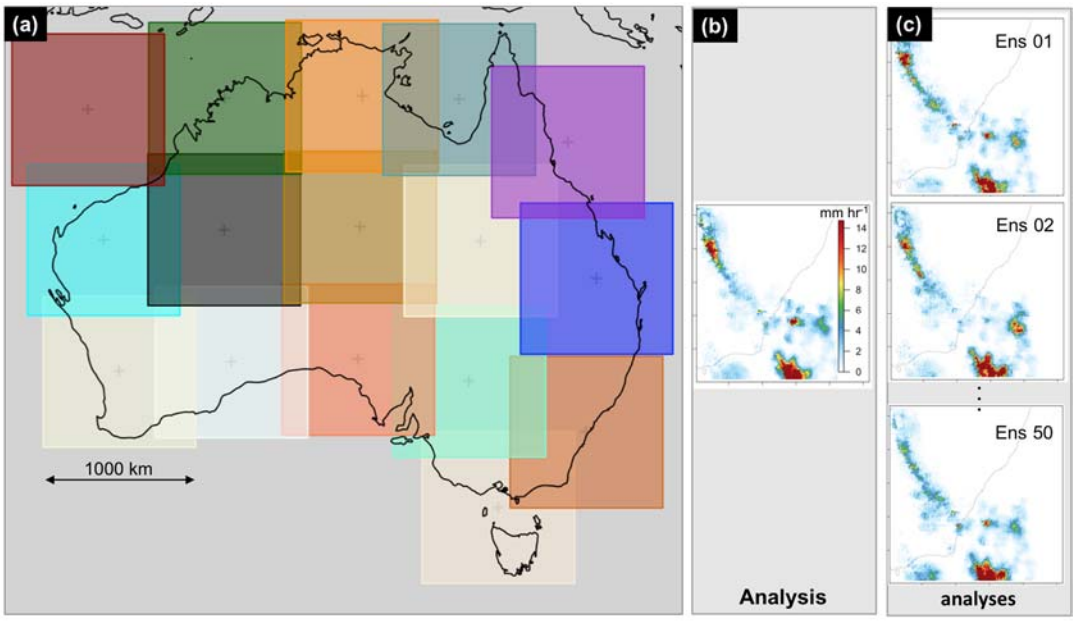

Figure 6. National application of the blending method and ensemble generation: (a) 1000 km x 1000 km tiles; (b) blended rainfall analysis for the "Sydney tile"; (c) 50-member ensemble rainfall derived by perturbing the rainfall analysis with noise field possessing the same spatial structure.

A SEASONALLY COHERENT CALIBRATION (SCC) MODEL FOR POST-PROCESSING NUMERICAL WEATHER PREDICTIONS

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Calibration models are often employed to post-process forecasts from numerical weather prediction (NWP) models to reduce bias, produce reliable ensemble spread, and ensure coherence, that is, forecasts are not worse than climatology forecasts.

Calibrated forecasts should reflect seasonal variation in climatology and performance of the NWP forecasts. This may be achieved by establishing calibration models separately for individual months. In practice, however, establishing separate models for individual months is often not feasible because archives of NWP forecasts are too short (1-4 years). A common practice is to use just one calibration model for all year round. This can lead to calibrated forecasts that lack seasonal variation in climatology, especially when the underlying skill of the raw NWP forecasts is low, such as at long forecast lead times. Such calibrated forecasts are clearly unacceptable for locations where there is strong seasonality in climate. When used for hydrological forecasting, they could lead to poor hydrological forecasts.

In this study, we introduce a seasonally coherent calibration (SCC) model that can work with short NWP forecast data and yield calibrated forecasts that have observed seasonal climatology, regardless of the underlying skill of the raw NWP forecasts. We present the theory of the SCC model and demonstrate its efficacy using a case study of post-processing precipitation forecasts at a rain gauge in northern Australia.

ENHANCED FLOOD WARNING SERVICES USING ENSEMBLE FORECASTING

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In the communication of flood risk, it is important to highlight the most likely scenario as well as low probability high impact scenarios. It is no secret that forecasting is an inexact science, but to enable responders to make informed decisions with full knowledge of the probabilities and potential impacts the Bureau needs to effectively communicate the uncertainty in the forecast.

With the introduction of the Bureau's National Hydrological Forecasting System (HyFS), the Bureau's flood warning service has been using ensemble forecasting together with estimates of catchment conditions, historical flood information, and sensitivity analysis to better understand and describe uncertainties in its flood forecasts.

To date, ensemble flood forecasts have focused on the use of multi-model rainfall forecasts from the Bureau's ACCESS models, ECMWF and the enhanced guidance from NexGenFWS (GFE). The multi-model approach is illustrated in Figure 1.

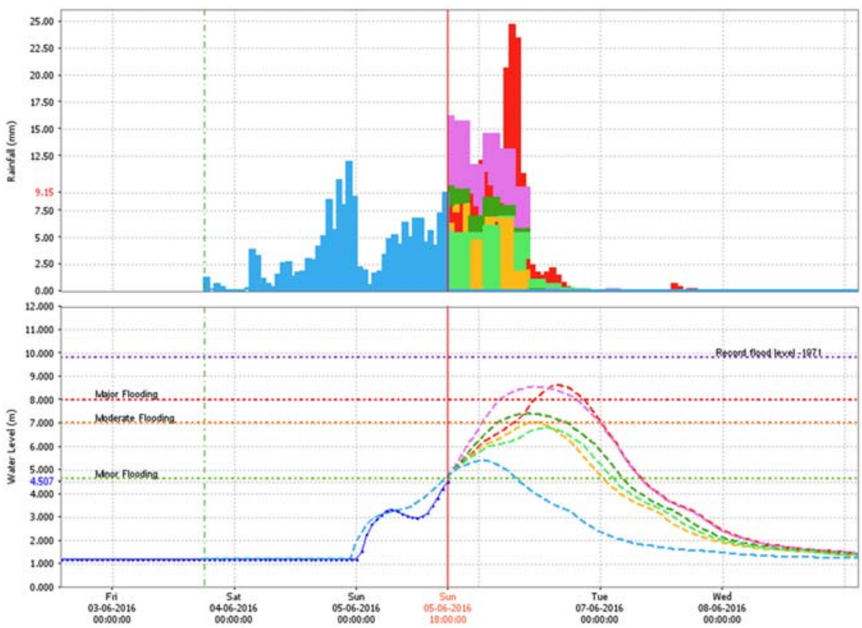

Figure 1: Illustration of multi-model ensemble forecasts currently available in HyFS. The red vertical line shows the current time with the coloured dashed lines showing forecast water levels from the different NWP and NexGenFWS (GFE) rainfall forecasts. The dashed blue line shows the expected water level with no future rainfall.

The multi-model approach has proved to be very successful in supporting the flood watch service, which provides the public and emergency services advice of increased flood risk up to four days in advance of flooding.

This year the Bureau will introduce a flood scenario service to complement the flood watch. Flood scenarios will provide a quantitative estimate of the flood risk for a "most likely" as well as a "credible alternative" scenario. Initially, these scenarios will use the current NexGen and deterministic guidance available in HyFS, but there is good potential to develop the service further to use a full ensemble approach. It is still early days, but one can envisage in the future that the Bureau could provide a full probabilistic flood scenario service using ensemble forecasting.

In developing flood forecasts and warnings, it is often the reality that the observed rainfall differs markedly from the multi-model rainfall forecasts available in HyFS. During high-end extreme rainfall events, the numerical weather prediction models are often poor at capturing the impacts of small-scale topography and embedded thunderstorms which drive extreme rainfall. Defensible flood warnings must supplement rainfall forecasts from NWP with input from meteorological forecasters, observations and nowcasting. To meet the requirement for nowcasting, the flood warning service has been exploring the use of ensemble forecasts from RAINFIELDS. Forecasts from RAINFIELDS are rapidly updated to account for the latest rainfall amounts and automatically merge nowcasts with extended range forecasts. The use of real-time observations and nowcasting is essential in providing credible and defensible flood forecasts.

The Bureau has been piloting the use of RAINFIELDS in the development of an extended lead time flood forecasting service for the Hawkesbury-Nepean Valley (HNV) (Figure 2). The pilot project aims to enable the emergency services to make informed decisions to allow them to commence evacuation at extended lead times. This project has been funded through Infrastructure NSW and developed in collaboration with WaterNSW and the NSW State Emergency Service. It is providing an ensemble based decision-making service that integrates flood intelligence and the Bureau's flood forecasts.

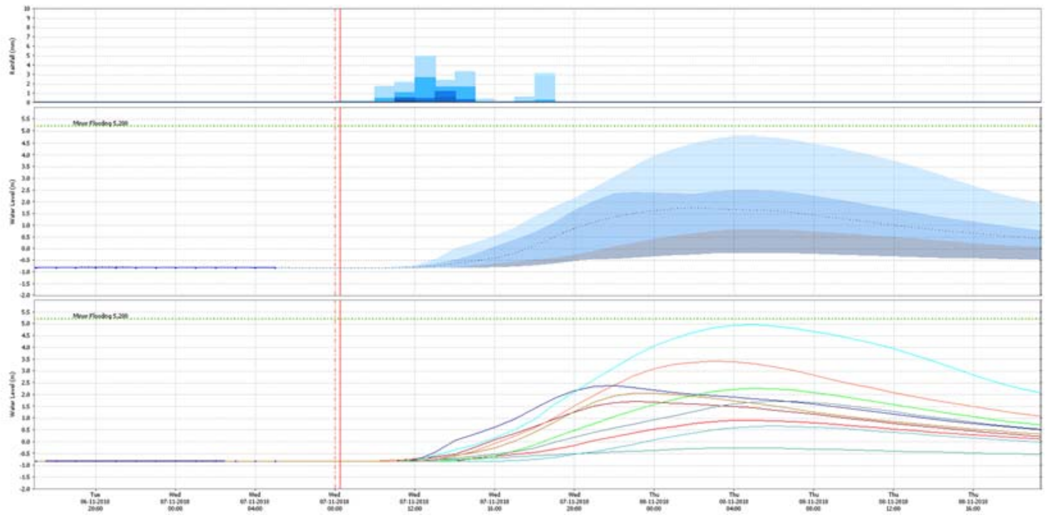

Figure 2: Illustration of RAINFIELDS ensemble forecasts in HyFS. The lower plot shows the time-series of flood forecasts with each coloured line representing an ensemble member. The shaded graphs show 10%, 25%, 75% and 90% probabilities of exceedance. The initial implementation uses a ten-member ensemble which will be extended to more than 30 members later this year.

This paper will explore the Bureau's flood warning service – and its path to providing enhanced flood warning services using ensemble forecasting approaches. In particular, it will highlight work that is underway to help our partner agencies and the community to make informed decisions with a full understanding of impacts and uncertainties

EXTREME WEATHER DESK – PRACTICES WITH ENSEMBLES

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Abstract

Increasing demands during periods of severe weather on the Bureau of Meteorology's (hereafter "Bureau's") operations were recognized early this decade. As a result, the Extreme Weather Desk (EWD) was developed in 2015 to provide a national focus for extreme weather capability, intelligence and services.

The core functions of the EWD include provision of;

- enhanced severe weather capacity during periods of sustained demand
- frontline communications
- development of new types of services through enhanced science to operations

The EWD is developing new services in impact based forecasting (National Hazard Outlook), convective forecasting (National Convective Outlooks and discussion) and fire weather services (Dry Lightning Outlook and PyroCB Potential Outlook). The use of ensembles to objectively provide information about forecast certainty in these development products has been a key focus for the EWD. How ensembles can be used to further develop such services will be a focus for this talk, particularly methods used to test the increased value of ensembles in Bureau service provision.

UNDERPINNING OPERATIONS, THE USE OF TECHNOLOGY IN NSW BUSH FIRE MANAGEMENT

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Introduction

The NSW Rural Fire Service established a formal Predictive Services capacity in 2010 with the commencement of the Fire Behaviour and Smoke Plume Modelling project. The Predictive Services capability has expanded rapidly with successive enhancements to now include a central unit of nine full time staff, four regional staff in addition to a project team of six RFS staff and two BoM staff working to improve the way fire danger ratings are calculated throughout the nation. The unit is equipped with 24 high quality Portable Automatic Weather Stations and 5 military standard Portable Atmospheric Sounding Systems.

Rapid expansion of the unit and significant gaps in modelling capability has driven a healthy appetite for the early adoption of new technology. Increasingly, new technology and research is leading to a shift from deterministic to probabilistic forecasting and the use of ensembles is being considered or already in use for the development of fire behaviour analysis products, seasonal outlook forecasting, bush fire risk management planning and the pilot of a new National Fire Danger Rating System.

Deterministic Vs. Probabilistic Forecasting

The use of fire behaviour science has been undergoing a shift in many fire Australian agencies from a system based on experience using hand drawn manual maps to one that increasingly uses simulators (Neale and May, 2018) and includes formal structures and training. A formal predictive services capability within agencies (particularly in NSW) has been a relatively recent feature. The philosophy of the NSW formal capability has been to underpin fire management decisions with the best available science.

A recent evaluation of simulator performance recommended a shift away from deterministic forecasting due to evaluated simulators sensitivity to weather and in particular wind (Faggian et.al., 2017). In NSW, manual forecasting has been used as the primary method for predicting fire behaviour with simulator predictions prepared independently to act as a validation source. The manual prediction method is considered better able to incorporate rapidly changing intelligence and encode uncertainty to provide a best estimate prediction of anticipated fire behaviour.

Despite the ability for a human to consider uncertainty, there still may be decisions required by an analyst that may be better represented using probabilistic forecasting. Experiential learning has led to the development of ensemble based products using simulators. Figure 7 provides an example of such products. These products provide the ability to vary inputs to account for uncertainty.

Use of New Technology

Use of rapid temporal resolution remotely sensed data such as frequent linescans and Himawari-8 satellite imagery has led to increased situational awareness for all levels of the organisation. For Fire Behaviour Analysts, it also provides a unique ability to calibrate models both in operational and research modes.

Situational Awareness is also significantly enhanced by the use of a fleet of Portable Automatic Weather Stations and Portable Atmospheric Sounding Equipment. This equipment providing the ability for Fire Behviour Analysts (and weather forecasters) to detect dangerous fire weather phenomena, leading to improved fire fighter and community safety.

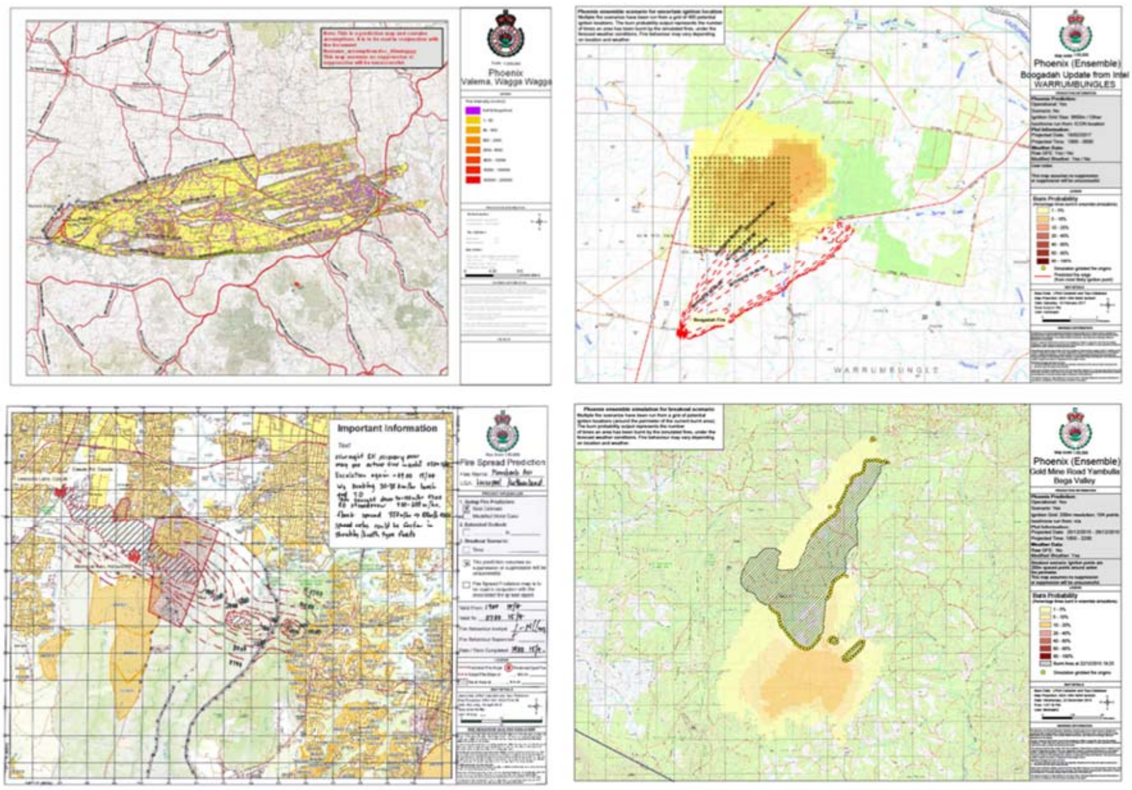

Figure 7 Examples of Fire behaviour prediction products and the use of ensembles in operational use in NSW

Use of Ensembles

A program to establish a new National Fire Danger Ratings System has been endorsed by the Australia New Zealand Emergency Management Committee. The system depends on calculations using fuel information and weather forecasts (Figure 2), both of which are uncertain. Ensembles could be used to understand confidence of rating forecasts, for example Category 4 with 10% change of Category 5.

The use of ensembles could also help to mitigate the issues caused by needing to have cut-offs between categories, which are currently handled informally using ‘discretionary range’.

Plans are being implemented for the next generation of Bush Fire Risk Management Planning in NSW to be underpinned by bush fire simulators. These simulator engines are the same as those used for forecasting and suffer from the same issues identified by Faggian et.al. (2017). The use of ensembles will also benefit risk planning by reducing uncertainty associated with the inputs.

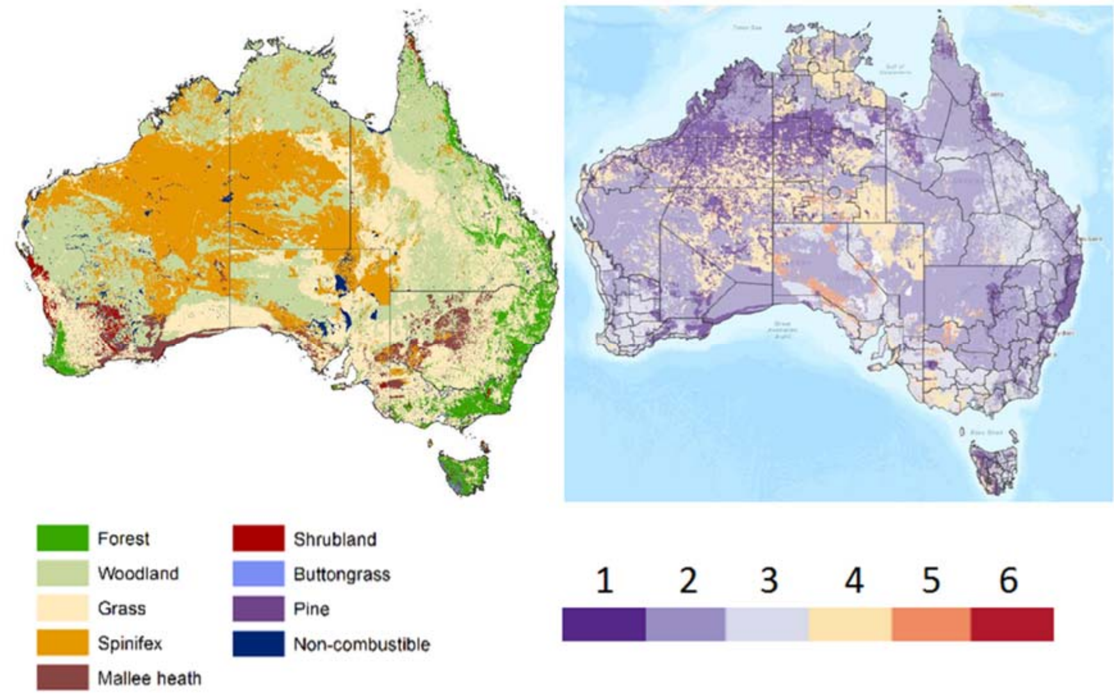

Figure 8 Research Prototype National Fire Danger Rating System. Left) Fuel types, Right) Sample ratings map.

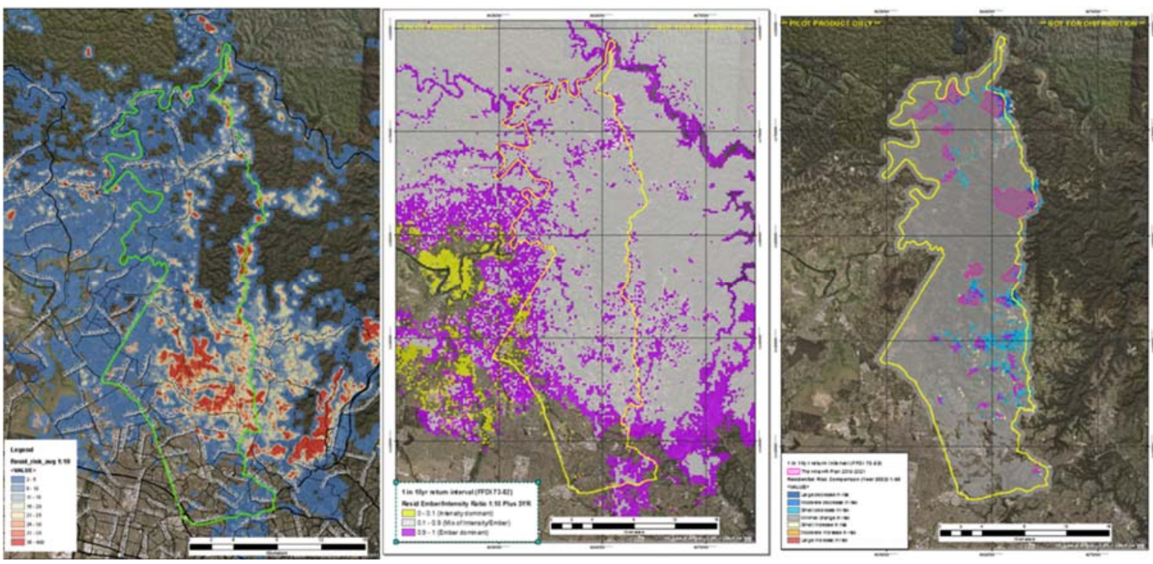

Figure 9 Use of simulators to forecast probabilistic risk

Conclusion

There are still many gaps in fire behaviour knowledge and modelling capability. New technologies are emerging which have the ability to overwhelm users of the products with data. Interpretation and utilisation of these outputs for fire behaviour predictions will be a challenge for the NSW RFS Predictive Services Unit. The unit is uniquely positioned to help the NSW RFS navigate the challenges and improve our ability to underpin operations with the best available science to improve safety outcomes for operational personnel and the community as a whole.

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DEVELOPING A SOURCE RIVER OPERATIONS TOOL FOR THE RIVER MURRAY SYSTEM

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The MDBA, with support from eWater, are developing an operations model of the River Murray system using the eWater Source platform. The ultimate aim is to provide a superior river operations decision support tool defined by automated real-time data integration, improved routing of river flows, integration of latest forecast technologies, and time efficient exploration of scenarios. In the new era of environmental water planning and delivery, the ability to explore alternative operational scenarios is becoming more and more desirable.

The **Source River Murray System operations model** was seeded from the Source River Murray System planning model — developed to support the implementation of the Murray-Darling Basin Plan and Sustainable Diversion Limits. Whilst the founding network configuration and parameters of the two models (operations and planning) are very similar, the scope and functionality of the operations model has been necessarily refocused.

River operators reside firmly in 'the now' of today and the immediate future. They make analyses on a daily or sub-daily basis, looking at current conditions, a range of forecast information and by testing scenarios. This helps to assess risks and understand complex trade-offs associated with each operational decision. Their focus is on the path ahead and a need to understand what may or may not occur depending on future conditions and the operational decisions they make. Model, workflow and analysis requirements are therefore fundamentally different to those of water resource planners or catchment managers trying to support long term policy decisions. This means data requirements and software user needs are different, and any operational decision support or modelling tool must function effectively within a range of dynamic operational and data work flow processes.

Important requirements include:

- functionality for quickly comparing a range of scenarios, including different inflow, demand and 'loss' forecasts by adjusting forecast conditions, and reviewing outcomes
- a clear and reliable interface to 'drive' the system by adjusting model parameters and interrogating results
- an efficient and robust process for ingesting operational hydrometric data of variable quality and completeness
- a means of exporting model scenarios and outputs for later reference and to use in reporting and other processes

Work thus far has gone a long way towards meeting these requirements, but there is still more to do. On-going testing and development by the MDBA has identified a range of critical user functional requirements and improvements that are specific to the use of Source in operations.

These are being implemented systematically by eWater and are expected to boost performance and further improve suitability of Source as a river operations decision support tool.

Other challenges go beyond configuring the model and refining the software capability. For example, to address operational data quality and workflow needs, MDBA staff have significantly expanded capability of their River Operations Workflow system. This is MDBA's primary hydrometric data workflow tool and is based on the Deltares FEWS system. This work has improved data provision for the Source model by integrating Source into existing workflows, improving data quality and ensuring latest data is reliably available for use in Source on a daily basis.

VALUE OF ENSEMBLE MODELS IN PLANNING THE ENERGY MARKET

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Abstract

AEMO is responsible for planning and operating the energy market. To fulfil this role AEMO forecasts demand and supply from 5 minutes ahead, the next season, and out to 20 or 30 years.

Focusing on the 20 to 30-year horizon, climate change is increasing temperatures and the frequency and intensity of extreme events. AEMO needs to plan the energy market for this future to ensure that the grid is sufficiently hardened to cope. The power system needs to operate 24 hours a day all year round. The challenges for the power system are not increasing average temperatures but rather increasing extremes temperatures (one in ten-year events). Extreme temperature events drive extreme electricity load events, stretching the supply fleet and stressing transmission infrastructure.

AEMO's planning role can be broken down into energy demand, supply, and network infrastructure:

- Supply and network assets de-rate at high temperatures reducing the amount of available generation and energy throughput of the network assets. High temperatures may also permanently damage network infrastructure. Further, sustained heatwaves reduce the ability of Generators to cool generation turbines.

- Demand increases during high temperature events driven by air-conditioner load. Heatwaves further increase energy demand as heat builds up in houses and apartments.

AEMO currently uses ensemble model results to plan the energy system in the presence of climate change over the next 20-30 years. Using the CMIP5 ensemble model results freely available on ClimateChangeInAustralia.gov.au AEMO downscales the projected daily maximum temperature data to half-hourly frequency using a quantile-quantile mapping algorithm. AEMO uses the half-hourly projected temperature data to forecast maximum demand percentiles out 20-30 years. AEMO uses every ensemble member in projecting the distribution of maximum daily temperatures treating each ensemble member as a separate simulation of the future.

For planning network and supply assets AEMO uses the threshold calculator on ClimateChangeInAustralia.gov.au to calculate the average number of days above 35-40 degrees per year. In the 2018 Integrated System Plan (ISP), AEMO assessed whether the operating limits of the network infrastructure today would be adequate for the climate in 30 years' time.

The global climate models represent spatially averaged temperature data. Due to this, the model data has lower extremes when compared to temperature observations from a single weather station. AEMO needs to understand temperature extremes at spatially discrete locations to understand the resilience of the energy system to cope with these extremes. AEMO is continuing to work with the Bureau of Meteorology to further downscale the ensemble model data so that the model data has extremes of similar magnitude to extremes experienced at a range of weather stations across the National Energy Market.

In addition to considering temperature projections, AEMO considers other weather metrics, although is less advanced in our understanding, including wind, rainfall and bushfire for hardening the energy system for climate change.

USE OF ENSEMBLES IN TROPICAL CYCLONE FORECASTING

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Tropical cyclones are a major natural hazard that affects Australian communities, emergency services, and industries. Ensemble guidance is an integral tool that allows Australian Bureau of Meteorology (ABoM) forecasters, whilst under tight time constraints, to provide skillful and reliable track and intensity forecasts for tropical cyclones.

Ensembles are used in a variety of modes in the tropical cyclone forecast process. One of the more valuable uses of ensembles is to characterise the uncertainty in the position of a tropical system on a particular day (Fig. 1).

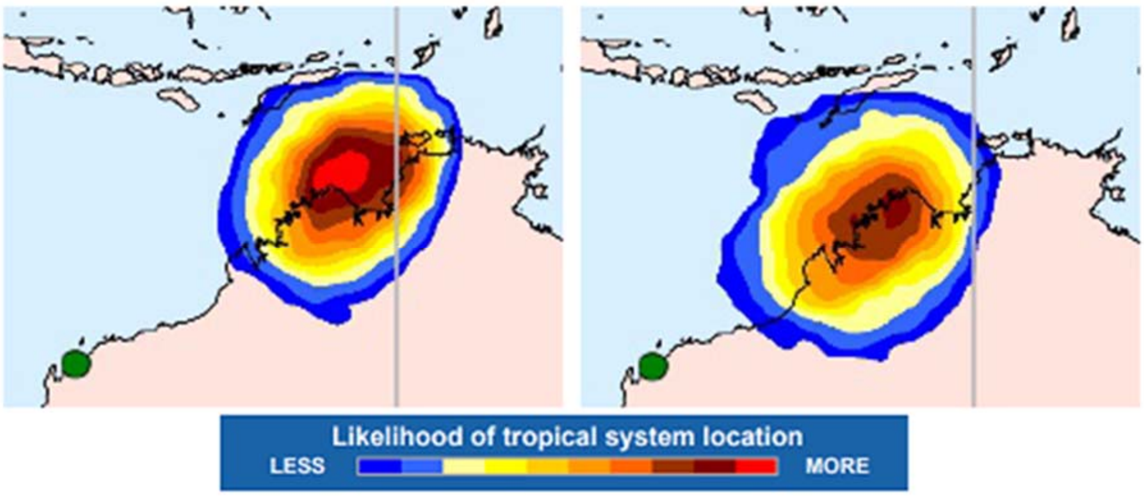

Fig. 1. These images indicate the spread of ensemble tracks from the ECMWF 12UTC 3rd March 2017 model run. For each point on the map, the number of ensemble members are counted that have a system which, at some time in the 24 hour forecast period, is both within 100 nm of that point and of 25 knots or greater intensity. The number of counted ensemble members is then converted to a percentage and that spot on the map is shaded according to the colour scale. The spread of ensemble tracks for the 24 hours of Monday 6th March (left) and Tuesday 7th March (right).

Future use of ensemble forecasts in operational tropical cyclone forecasting

Tropical cyclone track forecasting is a manual process that can be time intensive. In the future the ABoM forecasters are interested in automating the track and uncertainty area forecasting processes in the tropical cyclone warning centre. The automation of the track and uncertainty forecast process is likely to be achieved in the future through the uses of ensemble forecasts.

USE OF ENSEMBLES IN THE ENERGY AND RESOURCE SECTOR FORECASTS

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Applying ensemble guidance to offshore weather forecasts

Ensemble weather models are utilized for their ability to provide a range of probabilistic outcomes. There is a shift from the customers in the resource sector (mainly offshore NW Shelf oil and gas customers) to require more probabilistic forecast products to better align with their planning and risk management assessments. Products such as the P5 (5% probability) forecast and POE (probability of exceedance) forecast are examples of these.

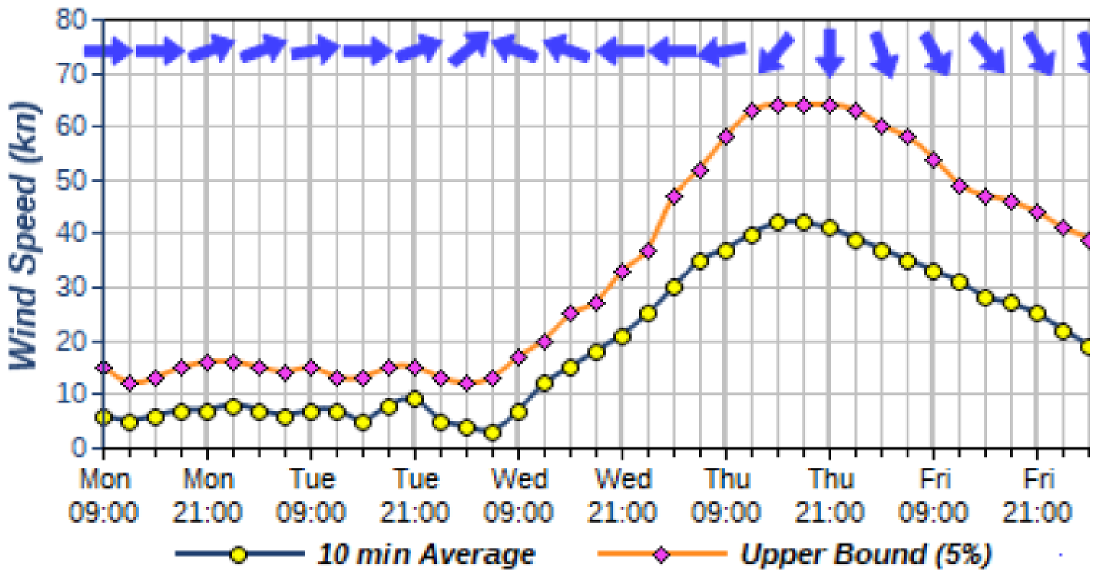

Figure 1: Example graph showing average 10m wind speed and P5 upper bound (5%) for a site

DRM – A (METEOROLOGICAL) OUTCOME OF ENSEMBLE MODELLING

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From a meteorological perspective, Disaster Risk Management (DRM) could logically be perceived as the outcome of modelling the meteorological parameters of weather events that are likely to have high impact on particular communities or areas, once that modelling has been interpreted by forecasters and disaster managers. To ensure that DR managers develop appropriate warning systems and responses to high impact events, they must have a comprehensive understanding of the likely outcomes that weather will have on the people or infrastructure which is vulnerable. Vulnerability is determined from the results of past events and increasingly, by modelling extreme meteorological conditions and applying the results to models of impacts. As such, ensemble modelling is becoming an increasingly important tool not only in forecasting the weather, but in assisting in the development of appropriate community responses. It is becoming increasingly apparent that at no time in human history is this more important or relevant than it is now.

According to a recent joint United Nations Office of Disaster Reduction (UNISDR)/Centre for Research on the Epidemiology of Disasters (CRED) report, between 1998 and 2017 climate-related and geophysical disasters killed 1.3 million people and left a further 4.4 billion injured, homeless, displaced or in need of emergency assistance. While the majority of fatalities were due to geophysical events, mostly earthquakes and tsunamis, 91% of all disasters were caused by floods, storms, droughts, heatwaves and other extreme weather events.

In 1998-2017 disaster-hit countries also reported direct economic losses valued at US$ 2,908 billion[1], of which climate-related disasters caused US$ 2,245 billion or 77% of the total. This is up from 68% (US$ 895 billion) of losses (US$ 1,313 billion) reported between 1978 and 1997. Overall, reported losses from extreme weather events rose by 251% between these two 20-year periods (UNISDR 2018).

Despite significant progress in strengthening early warning systems across the world, often by making use of advances in science and technology, including ensemble modelling, unmet needs remain. The UNISDR report shows that disasters are increasing in frequency and severity in most areas, with climate change and variability exacerbating the situation. Many developing countries, in particular least developed countries (LDCs), small island developing states (SIDS), and landlocked developing countries (LLDCs), have not benefited as much as they could have from advances in the science, technology and governance behind early warning systems. Significant gaps remain, especially in reaching the "last mile" - the most remote and vulnerable populations

[1] All economic losses and GDP are adjusted at 2017 US$ value

at the community level with timely, understandable and actionable warning information), including lack of capacities to make use of the information. The resulting societal benefits of early warning systems have thus been spread unevenly across regions, countries and communities. DR Reduction (DRR) is what DR managers aim to achieve and DRR is a focus of many activities and agreements around the world including possibly the foremost strategy - the Sendai Framework for Disaster Risk Reduction 2015-2030 (UNISDR, 2015).

DRR is central to the World Meteorological Organization's mission and WMO has a number of projects that are aimed at assisting their Members in obtaining and sharing improved, timely and useful meteorological, hydrological and climate data and warning information. Projects such as the Global Multi-hazard Alert System (GMAS), the Severe Weather Forecast Demonstration Project (SWFDP), the Flash Flood Forecasting Guidance System (FFGS), the Integrated Drought Management Program (IDMP) and the project to characterize and catalogue extreme weather, water & climate events, which is being developed to assist Members in measuring the events and their impacts, are examples of these and a few will be touched on during the presentation.

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(from https://www.unisdr.org/we/inform/publications/43291)

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ADVANCES IN THE BUREAU'S DISASTER MITIGATION POLICY

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The Bureau's Public Safety Program is primarily concerned with ensuring the safety of all Australians. Essentially the focus is on the prevention of loss of life and reducing damages from natural hazards by providing services to the Australian community. These services are provided directly and in close collaboration with jurisdictional emergency management agencies, the Department of Home Affairs, Insurance Industry and critical infrastructure managers. Disaster Mitigation Policy has a key role in ensuring that broader national policy drivers, partnerships and priorities are realised through the delivery of Bureau services. This paper will provide an update on advances within the Bureau's disaster mitigation policy and some of the key initiatives driving change.

IMPROVER – THE NEW MET OFFICE INTEGRATED POST-PROCESSING AND VERIFICATION SYSTEM

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Post-processing systems face a number of challenges. The development of ensemble systems and convection-permitting forecasts changes the nature of the data processed and the type of corrections that need to be made. Automated products need to be of high quality, frequently updated, and consistent across diverse communication formats. The Met Office is building a new post-processing system to address these challenges and provide a modern, efficient platform for future development. The core processing operates on gridded probabilistic information, with consistent spot forecasts extracted at the end. Prototype chains have been developed for the main surface variables, including science developments such as topographic neighbourhood processing and estimation of whether snow would melt before reaching the actual ground level as opposed to model orography. The system is designed to provide both automated forecasts of ordinary weather for the public and “heads-up” warnings of severe weather for operational meteorologists.

The new system integrates verification at each stage, to assess the impact of each component on a broad range of metrics. Probability and percentile forecasts are converted back to ensemble members, allowing the full range of ensemble verification scores to be applied. The same configuration that will run operationally can also be run in historic trials, allowing new developments to be evaluated and tuned in advance, as is common practice for Numerical Weather Prediction (NWP) systems. This statistical feedback is particularly important given the focus on probabilistic predictions, whose full assessment requires a corresponding distribution of outcomes assembled over many cases. The IMPROVER verification infrastructure thus helps to improve the robustness and efficiency of the scientific development process. This will be illustrated using the results of some early trials and tuning experiments.

USE OF ENSEMBLE GUIDANCE FOR OPERATIONAL FORECASTING

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The Australian Bureau of Meteorology is proposing to provide a seamless routine national forecasting service from two centres instead of the current 7 State-based offices. A related goal is to automate as much of the routine forecast production as possible over the next couple of years, so that forecasters can focus on providing the highest value services. That is also the common intention or practice of overseas Meteorological Agencies. In the Bureau, this has required probabilistic post-processing of rainfall guidance that is good enough to support the automation and increase forecast skill. The Bureau is also looking to post-processing to help maximise the benefits of the investment in ensemble modelling and support enhanced risk and impact-based services to the community.

In order to provide better and more cost-effective risk-based post-processing, the Bureau is actively pursuing a collaboration with the UK Met Office on their 'IMPROVER' framework.

Increased automation of operational forecasting and the development of probabilistic services throws up issues to be worked through; several examples will be discussed.

THE USE OF PROBABILISTIC FORECASTING IN ANTARCTICA

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Introduction

Responsibility for the delivery of Australia's Antarctic program rests with the Australian Antarctic Division (AAD). The program of activities is managed by AAD staff at their headquarters in Kingston, Tasmania and delivered from the Antarctic stations by a mostly transient 'expedition' workforce. This year (2018-19) marks the 72nd Australian Antarctic expedition.

The AAD run four permanent, year-round research stations: Casey, Davis, Mawson and Macquarie Island. Travel between mainland Australia (typically Hobart) and the stations is either by icebreaker, commercial Airbus A319 jet or by Royal Australian Air Force C17. On the icy continent, travel between stations and into remote field camps is by overland tractor convoy, or air transport, with helicopters and fixed wing aircraft such as Basler, Twin Otter or LC130. Due to the long darkness and higher frequency of extreme weather conditions over the winter period, travel is generally restricted to the October-March 'Summer' season. Winter activities are usually restricted to the station, except for the occasional overland traverse to monitor remote penguin colonies, maintain Automatic Weather Stations or recreational purposes at field huts. In contrast to equivalent activities conducted in mainland Australia, the AAD's operational risks are significantly magnified due to the remoteness from help if needed and higher frequency of harsh weather in Antarctica.

With a view to improving operational efficiency and mitigating risks to life and property, the Bureau has embedded 'decision support meteorologists' into the Australian Antarctic program every summer season since the early 1990's. Currently four operational meteorologists are recruited from within the Bureau's State or National Forecast Centers, and a fifth meteorologist from the Royal Australian Navy. The forecasters undertake a 4 week long Antarctic competency training and assessment program prior to deploying into the expedition. The course focuses on the dynamical, physical and climatological aspects of key hazardous weather phenomena, such as severe wind events, blizzards, freezing fog, cold snaps and precipitation (including clear sky precipitation or diamond dust). The pre-departure training also considers the adequacy of in-situ and remotely sensed observational platforms as well as the skill of Numerical Weather Prediction output. Station leaders, pilots, operations coordinators and ships masters are also invited into many training sessions to provide insights into the critical weather thresholds that can affect their activities (see table 1). Armed with these insights, the meteorologists are then embedded into the expedition to support all expeditioners with their weather sensitive decisions. The Bureau's embedded Antarctic service has become increasingly valued by the AAD. Simply put, the service underpins the safe and efficient running of their program.

Table 1 – Significant Weather Thresholds for General Aviation (guidance only)

Significant Thresholds

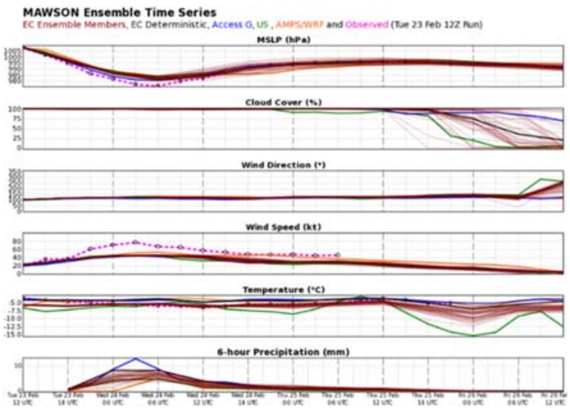
- Wind > 15kt (any direction)
  - Possible reduced surface contrast due to drifting snow.
  - May need ice screws on landing to secure aircraft if surface is slippery.
- Wind > 15kt (crosswind component)
  - May inhibit takeoff/landing (depending on aircraft type)
- Wind > 30kt
  - Likely reduced visibility, surface contrast and horizon definition due to blowing snow.
- Wind gusts > 48kt
  - Need to tie down fixed-wing aircraft.
- Mean winds > 50kt or gusts > 60kt
  - Tie down/stow helicopter blades (but can only de-blade if wind < 25kt).
- VFR restrictions (apply to most Antarctic aviation):
  - BKN/OVC cloud with base below 1000ft
  - Visibility < 3000m
  - Surface or Horizon Definition "Nil"
- Helicopter cloud restrictions:
  - Helicopters operating in Charter Category (most AAP operations) require a minimum altitude of 500ft. Helicopters only need to keep clear of cloud – not maintain a specific vertical separation – so if flying at 500ft the cloud base could legally be at 550ft.

The Use of Ensemble Prediction Systems in the Antarctic

Our Antarctic meteorologists are increasingly making use of Ensemble Prediction System output, specifically from the European Centre for Medium Range Weather Forecasts (ECMWF https://www.ecmwf.int/) and the Antarctic Mesoscale Prediction System (AMPS WRF http://www2.mmm.ucar.edu/rt/amps/), to better frame the likelihood of operational thresholds being breached.

Graphical point time series using non-bias-corrected ECMWF EPS and deterministic global NWP output by ACCESS G, AMPS WRF, NCEP GFS are issued daily to the stations (fig 1).

Figure 1



Training in the interpretation of the graphical time series is provided to expeditioners pre-departure and further instruction is possible with the forecasters and observers at the stations. A pamphlet on EPS use is being developed for future expeditions. Wind strength, temperature and precipitation are the key parameters of interest. Gross errors in those parameters are not uncommon as highlighted in the wind speed time series of figure 1, where 1 minute mean winds of 60 to 80 knots were observed (pink dotted line) over an 18 hour period on Wednesday the 24th whilst all NWP guidance ranged between 30-50 knots for the same period. Whilst biases in some parameters (such as pressure) could be corrected, there are dynamical and numerical reasons why wind speed and temperature cannot without great effort. This limits the value of direct model output in servicing high risk activities. The graphic is however not without value, as it is automatically generated (low cost), and conveys weather trends and anticipated forecast confidence through member spread. So it effectively assists routine schedule planning, such as for carpenters wanting to work on a roof 'sometime this week' and other such local area operations. All weather related high-risk activities are however supported by our meteorologists.

Conveying the 'real' likelihood of operational thresholds being breached

The Bureau's Antarctic services include three distinct products that highlight the likelihood of an event occurring:

- aviation *TAF* for fog (prob30 and prob40);
- warnings of *Blizzard/Gale risk* in station (public weather) forecasts; and
- in our *Operations Support Briefs* (table 3).

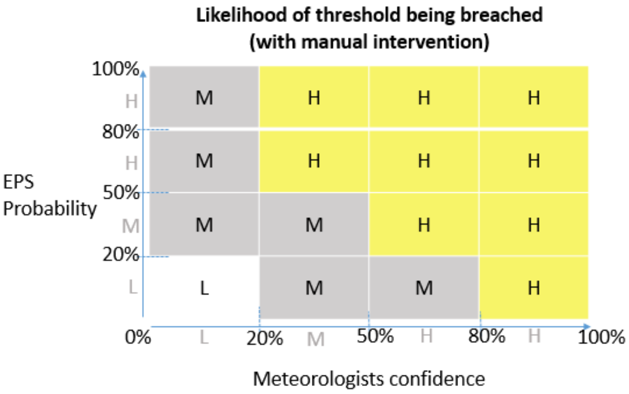
For consistency across our Antarctic products and therefore ease of use, the likelihood of operational thresholds being breached has been set at:

- Low: 0-20% chance of occurrence;
- Moderate: 21-50% chance of occurrence;
- High: 51-100% chance of occurrence.

The setting of likelihood levels was informed by thunderstorm and fog probability levels for aviation Terminal Aerodrome Forecasts (TAF) and through consultation with Antarctic decision makers.

However, because our experience has shown that direct NWP output alone lack sufficient skill to quantify/qualify the likelihood of a weather threshold being crossed, we require the additional consideration by the meteorologist to establish the forecast/warning. A matrix has been developed to standardise the assessment of likelihood between forecasters (table 2).

Table 2 – Likelihood Matrix



For an example of it's use, consider a meteorologist trying to establish the likelihood of a blizzard impacting Casey Station (a blizzard being defined as: *10 minute mean winds >34 knots; horizontal visibility <100metres; sub-zero Celcius temperatures and duration of at least 1 hour*). The EPS output may have 60% of it's members meeting these criteria whilst the meteorologists confidence may be set at only 30% (via gut feeling, experience and in some cases with support from a decision making tree). The EPS's *high confidence* and Meteorologist's *moderate confidence* combine to result in a *high likelihood (and therefore >50%)* of the event occurring. It is noteworthy that the matrix is skewed to the meteorologists preference, thus allowing one to warn of the high likelihood of an event occurring despite all ensemble members not meeting the threshold.

Table 3 – Operations Support Brief example

Operations Support Brief - Davis

Issued: 3:43 pm Davis local time (08:43 UTC), Tuesday 13th November 2018
Issuing office: Davis
Valid: 14th November to 17th November 2018

Australian Government
Bureau of Meteorology

	Wednesday 14th November	Thursday 15th November	Friday 16th November	Saturday 17th November
Locations:				
Davis (Helo and Basler)	Nil Significant Weather	BKN 1500/5000 and snow showers after 12Z. SFC Poor after 12Z, HZN Fair.	BKN 3000/7000 with snow showers. SFC Poor, HZN Fair. Nil significant weather after 12Z	Nil Significant Weather
Vestfolds (Helos)	Nil Significant Weather	BKN 1500/5000 and snow showers after 12Z. SFC Poor after 12Z, HZN Fair/Poor.	BKN 3000/7000 with snow showers. SFC Poor, HZN Fair/Poor. Nil significant weather after 12Z	Nil Significant Weather
Wilkins Runway (Basler)	FEW/SCT 1000/8000 ft from 03Z, SCT/BKN 1000/14000 ft from 06Z. Light snow showers from 03Z. SFC/HZN: Fair/poor.	BKN 1000/14000 ft AGL. Snow showers. SFC/HZN: Poor.	E/NE 15/25 knots until 03Z. Drifting snow possible.	Nil significant weather.
Routes: *(note conditions above for sites)*				
Wilkins-Davis-Zhongshan (Basler)	FEW/SCT 6000/18000 ft on ascent from Wilkins. FEW/SCT 9000/15000 ft between 102E and 85E. 10000 ft winds ASL E 15/25 knots.	SCT/BKN 2000/14000 ft ASL E of 105E. SCT/BKN 8000/14000 ft ASL between 105E and 93E. SCT/BKN 3000/7000 ft on descent into Progress. Snow showers until 93E and on descent into Progress.	SCT/BKN 9000/15000 ft between 104E and 81E.	Nil significant weather.
Note: This document is issued daily to SLs and Ops Coordinators for planning purposes. It captures the salient conditions for weather sensitive operations planned over the forecast period. This planning product does *not* replace station, field camp, marine or aviation forecasts.				
Good: Greater than 80% probability of conditions better than operational thresholds. **Marginal:** 50%-80% probability of conditions better than operational thresholds. **Caution:** Less than 50% probability of conditions better than operational thresholds.				

Conclusions and Comments on the future

Probabilistic forecasts have become highly valued by Antarctic decision makers, particularly as they assist in the weekly planning of transport activities and help the understanding of exposure to high impact weather. It must be noted that the effective use of probabilistic forecasts has required extensive investment in both user and forecaster education as well as in collaborative design of the products. Not every decision maker was on board and still today some only want to know 'what will happen' rather than a range of possible weather outcomes. Some decision makers also prefer the meteorologist to 'stick to the weather' and not extend *our* advice onto operational impacts as per our Operations Support Brief (table 3). However, on the whole, probabilistic forecasts significantly contribute to the overall success of the Bureau's Antarctic services and are becoming increasingly so as model output, user skill and product 'useability' improve.

A current challenge to 'useability' is integrating multiple EPS's into one viewer or graphic. For example, currently the Bureau acquires two distinct ECMWF EPS datasets (one north and the other south of 60ºS) which causes disconnections in maps and warps some statistics when combined. Also, the AMPS WRF EPS is currently only available on a web display which makes it difficult to compare with ECMWF EPS output.

The inability for EPS output to skilfully represent high impact weather also limits its usefulness. The likelihood matrix (table 2) attempts to address this shortcoming by also considering the opinion of the meteorologist before advising on the likelihood of key operational thresholds being breached. The matrix, particularly when used with other decision support systems, also attempts to standardise the calculation of probability across our transient workforce.

Because it was co-designed with Antarctic decision makers, the qualification of likelihood levels at low: 0-20% chance; Moderate: 21-50%; and High: 51-100% is not consistent with Bureau mainland "chance of rain" qualifiers of slight: 15-24%; medium: 35-64%; high: 65-84% and very high: >85%. One could argue for standardisation.

USE OF CONVECTION-ALLOWING MODEL ENSEMBLES IN FORECASTING SEVERE CONVECTIVE HAZARDS

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Only just over one year ago the Australian Bureau of Meteorology moved into production its first ever true convection-allowing model (CAM), the ACCESS-City model (APS2 edition). This model provides exciting new avenues for the prediction of severe local convection in the form of explicitly generated pseudo-storms on the 1.5 km model grid. Casting these storms through the lens of simulated radar reflectivity allows subjective and objective comparisons to observed storms on radar, and allows for a quick human appraisal of otherwise very complex model output.

A noteworthy advance in the utility of CAMs for the prediction of severe convection transpired well over decade ago inspired by an annual Hazardous Weather Testbed at the National Weather Center in Norman, Oklahoma. The most severe explicitly generated and realistic-looking model storms produced strong updrafts (large updraft speeds) collocated with storm-scale rotation (assessable through the relative vertical vorticity). A simple product of these two quantities, integrated over the 2-5 km above ground layer (a layer in which storm-scale rotation is most often observed on Doppler radar) became known as updraft helicity (UH) and, to this day, has been the most successful proxy for supercells and its hazards modelled in CAMs.

Hourly or multi-hourly maxima of UH (with the maximum taken over UH values at every model time step) can be used to create a range of very useful proxies for high-end severe convection, such as maximum UH products, storm tracks or UH neighbourhood probabilities. These proxies can easily be extended into CAM ensembles to account for the timing, placement and intensity uncertainties inherent in any individual CAM integration.

The presentation will focus in how CAMs and CAM ensembles can be employed to predict severe convection out to 1-2 days in advance through utilising simulated reflectivity and updraft helicity output.

INCORPORATING SATELLITE OBSERVATIONS INTO A VOLCANIC ASH DISPERSION ENSEMBLE PREDICTION SYSTEM

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In support of the operations in the Darwin Volcanic Ash Advisory Centre (VAAC), the Bureau of Meteorology (BoM) is investing in the development of the Dispersion Ensemble Prediction System (DEPS), an operational modelling system for the forecasts of volcanic ash (e.g. Potts et al. 2017). The current version of DEPS uses an ensemble of NWP forecast data, mostly from the BoM's ACCESS model suite, to drive the National Oceanic and Atmospheric Administration's (NOAA) Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) dispersion model (Stein et al. 2015) and produce a probabilistic forecast of ash dispersion that accounts for meteorological uncertainty. The ensemble is initialized from eruption parameters (e.g. volcano, plume height) input by the user via a web interface.

The next version of DEPS, currently in development, extends its capability by accounting for uncertainties in the source term. This is being done through the assimilation of observations into the ensemble forecast. Observations potentially come from two sources: i.) polygons of ash location produced by the VAAC as part of their advisories; and/or ii.) real time quantitative satellite ash retrievals from the NOAA Volcanic Cloud Analysis Toolbox (VOLCAT) system (e.g. Pavolonis et al. 2018). Incorporating both types of observations will allow for probabilistic estimates of the top and bottom heights of the plume along with quantitative estimates of the ash mass loading or concentration. These products are highly desired by the aviation industry to help manage the risks for flight operations and to ensure safety.

The performance of the system will be discussed in the relation to the eruption of Mt. Merapi in central Java, Indonesia on 11 May 2018, a short-lived eruption that extended a plume to approximately 8 km height. While the impacts of this event to aviation were localized, the relatively dry and mostly cirrus-free atmosphere at the time allowed for consistent, good-quality VOLCAT retrievals for over 6 hours and provides an excellent opportunity to evaluate DEPS as it is being developed. The presentation will discuss the impact that incorporating these observations has on the resulting forecast and highlight some practical issues around the use and interpretation of both quantitative satellite retrievals and advanced dispersion modelling techniques in an operational environment.

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EVALUATION OF NWP MODEL RAINFALL FORECASTS FOR THE 7-DAY ENSEMBLE STREAMFLOW FORECASTING SERVICE

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Abstract

The Bureau of Meteorology is planning to launch its national 7-day ensemble streamflow forecast service in mid-2019. Ensemble streamflow forecasts are generated using post-processed multi-model Numerical Weather Prediction (NWP) ensemble rainfall forecasts. In order to understand the characteristics of different NWP rainfall products, effects of rainfall and streamflow post-processing, and to identify capacity and efficiency of the operational forecast system, we evaluated four NWP rainfall products and corresponding streamflow forecasts for 26 catchments located in various hydro-climatic regions across Australia. The four NWP rainfall forecast products evaluated in this study are; (i) the Australian Community Climate and Earth-System Simulator – Global Ensembles (ACCESS-GE), (ii) ACCESS-G (deterministic), (iii) Poor Man's Ensemble (PME), and (iv) European Centre for Medium-Range Weather Forecasts (ECMWF). The evaluation results show that the rainfall post-processing reduces bias and improves the reliability of rainfall forecasts as well as the corresponding streamflow forecasts. Streamflow post-processing further improves the accuracy and reliability of forecasts significantly at shorter lead-times and the impact declines with the lead-time. Overall, the use of rainfall forecasts of ECMWF lead to better streamflow forecasts at the catchment scale. Further analysis on proper ensemble spread necessary to quantify forecast uncertainty reveals that 200 ensemble members are required from each ACCESS-GE and ECMWF products.

SINGLE-VALUED FORECASTS IN AN ENSEMBLE WORLD

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Although full and poor-man's ensemble approaches open the potential for weather services driven by rich probabilistic information, there will remain demand for single-valued weather forecast information, as a simple and familiar communication device. There are various approaches that can be used to provide a single-valued forecast service. These range from outputs of a single Numerical Weather Prediction model to forecasts derived from a consensus of different models.

We consider how the value to users of forecasts from different approaches is related to the error characteristics of the forecasts by combining the idealized concepts of Relative Economic Value (Richardson, 2000) and a Linear Gaussian Error Model (Tian *et al.*, 2016). When unconditional biases are removed, single-valued forecasts built from the mean of a consensus of Numerical Weather Prediction models benefit users interested in decisions near the climatological mean. This is due to their reduced spread of errors compared to the constituent models. Deterministic Numerical Weather Prediction forecast systems may provide benefits for users sensitive to extreme events if the forecasts have smaller conditional biases and hence better resolution of such events.

We conclude that where single-valued forecast services are used, basing them on a consensus is the best approach for routine decision making. However, there is a strong need to provide services which are more explicitly probabilistic, for extreme events and associated warning services.

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NWP ENSEMBLE VERIFICATION

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Abstract

In 2019 the Bureau of Meteorology (BoM) is planning to make operational a global numerical weather prediction ensemble system (EPS), Access-GE. This will be followed by city-scale EPSs, the Access-CE suite hopefully also in 2019. The arrival of these operational EPSs will be a milestone at the BoM but they must be fit for purpose.

Ensuring that new EPSs are indeed fit for purpose generally entails determining the characteristic strengths and weaknesses of such systems using subjective and objective verification methods. Subjective verification tends to be qualitative, for example, an EPS developer or a forecaster might 'eyeball' a range of EPS forecast charts to see if they 1) make physical/meteorological sense and 2) realistically capture past weather – including extreme or interesting events. Objective verification tends to be based on statistical measures of certain forecast attributes and is, therefore, quantitative in nature. Both verification approaches may involve inter-comparing the EPS of interest with other EPSs.

This presentation concerns objective verification which, so far, has focused on Access-GE. The verification will 1) inform development and operations teams whether Access-GE is ready to make the transition from development to operations and, once operational, 2) provide routine performance monitoring for operations and 3) provide the operational capability to meet WMO EPS verification reporting commitments.

We have adopted and implemented the WMO guidelines on global EPS verification [WMO] to meet all three of these aims. The verification measures in the guidelines are mature and represent a 'baseline' set of verification measures for the global EPS. Deterministic forecasts can be derived from an EPS so some of these verification measures are deterministic. Such measures may be simpler and/or familiar to new EPS users. However, in order to capture forecast uncertainty, the majority of EPS forecasts are probabilistic. Correspondingly many of the EPS verification measures reflect this probabilistic capability. Such measures may seem more complicated and/or less familiar to new EPS users. A small selection of these verification measures are described including preliminary verification results for Access-GE.

Having established an approach to objective verification for Access-GE next steps include identifying some opportunities and challenges EPSs may present for downstream users and associated verification needs. Downstream users include the BoM's guidance post-processing team, forecasters and external users. Some early thoughts for working with these users are outlined. Of course this process will then have to be repeated for the Access-CE suite!

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VERIFICATION OF PROBABILISTIC RAINFALL FORECASTS

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Abstract

We illustrate verification of probabilistic rainfall forecasts by presenting a sample of verification results for official forecasts which underlie those on the Bureau's external website. We compare these to verification of the same forecasts based on an ensemble of model outputs. We will present results for a three-month period, comparing forecasts to observations at automatic weather stations in Southern Australia. The data and main verification techniques are described in Griffiths *et al.*, 2017.

Our verification is motivated by a need to assess the suitability of the ensemble-based output to replace the official forecast to deliver the public service. As such, our verification is based on definitions of the service and this informs choices made in conducting the verification. For example, it informs the choice of observations against which the forecasts are assessed.

A complete suite of probability forecasts defines a probability density function. Our verification does not assess the whole probability density function at one time, as is done by the Continuous Ranked Probability Score. Instead, we focus on forecasts which form part of the public service. We assess the official and ensemble-based forecasts in ways that allow us to comment on their performance at different lead times and in different situations, or when being used for different purposes.

We present results for examples of two types of probabilistic forecast. One is the forecast of the Chance of Rainfall (%) exceeding 1 mm in a 24-hour period. The other is a percentile forecast, namely the amount of rain forecast (mm) which will be exceeded in a 24-hour period with a 25% confidence. The 25th percentile forecast is defined as 0 mm if the chance of any rain is $\leq$ 25%.

We use the Brier Score to verify the Chance of Rainfall forecasts. The Brier Score is the analogue to the mean square error which is popular for verifying single value forecasts. We use reliability diagrams to provide detail of bias conditional on the forecast values. We use relative economic value curves to explore the ability of the forecasts to distinguish rain from non-rain events, or heavy rain from lighter rain events, in a manner that is valuable to users of the forecasts.

Percentile forecasts are another view into the probability density function. As the percentile forecasts are a prominent part of our service we assess them directly, providing information about biases conditional on the forecast values.

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THE COPERNICUS ARCTIC MARINE FORECASTING CENTER

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Introduction

The Arctic Marine Forecasting Center (ARC MFC) is an ocean, sea-ice, wave, and bio-geochemistry forecasting and reanalysis system covering the Nordic Seas and Arctic Ocean North of 63°N (domain shown in Fig 1). The forecast system serves as the Arctic component of the Copernicus Marine Environmental Monitoring System and is run jointly by The Nansen Environmental and Remote Sensing Center and the Norwegian Meteorological Institute. The TOPAZ ocean and sea-ice model uses an advanced data assimilation (DA) technique (the Ensemble Kalman Filter, Sakov *et al.*, 2012) to constrain the system to six real-time satellite and in situ observational products. In addition to the dissemination of daily forecasts and a reanalysis, a broad range of product quality assessments are performed on weekly and quarterly intervals. The forecast system also includes a wave model which issues fluxes for the estimation of wave effects in the upper ocean as well (see conceptual overview of the forecast system in Fig 2).

Here we present the operational forecast system, its Ensemble Kalman Filter DA and the overall performance of the system. We will also present results from an experimental setup incorporating physical processes related to surface waves, notably parameterizations of Langmuir turbulence (Ali et al, 2018). Wave attenuation in ocean sea ice is also under development, and some preliminary results from different wave damping parameterizations will be presented

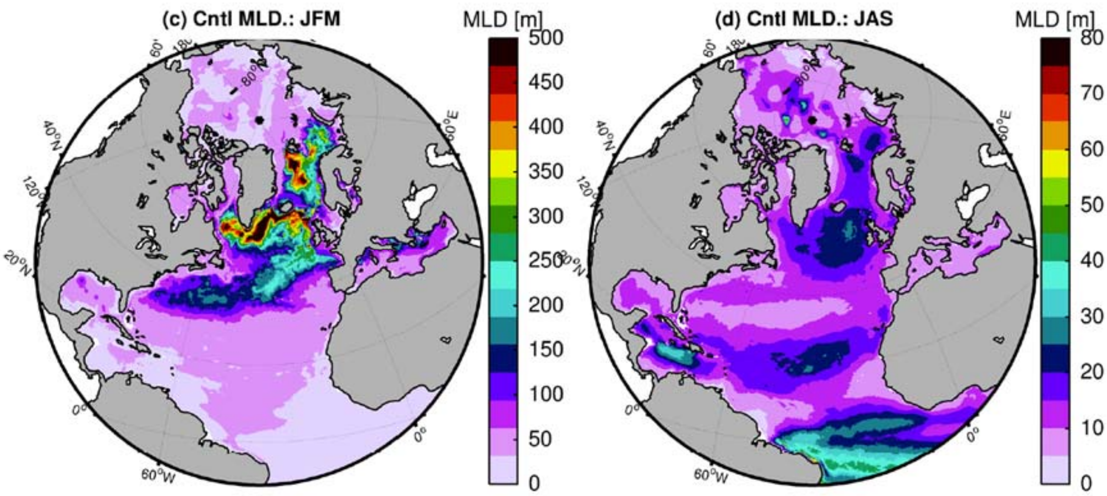

Figure 1. Mixed layer depth January-March (left) and July-September (right). The TOPAZ model domain used for ARC MFC covers the North Atlantic and the Arctic Ocean.

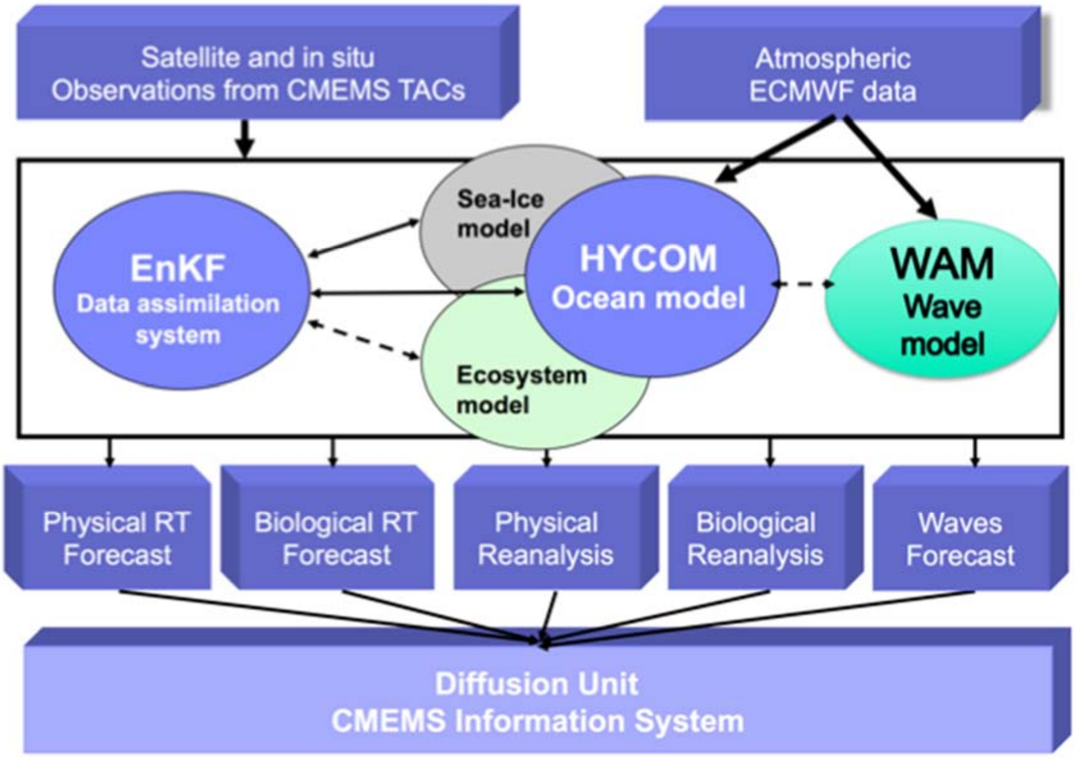

Figure 2. Conceptual overview of the ARC MFC forecast system and its EnKF data assimilation system.

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A DATA CONTENT SEARCH METHOD

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Abstract

Convolution Neural Networks (CNN) have demonstrated a high level of performance in the areas of image recognition and classification. The training of such networks over large corpora of imagery has facilitated additional applications such as content-based image searching and retrieval. Here we investigate the efficacy of applying a pre-trained deep CNN to the task of content searching within large environmental datasets. We show that the learned convolution filters from a pre-trained network provide sufficient fidelity and diversity to accurately perform a content search within a dataset that is unrelated to the CNN training data.

ENSEMBLE FORECAST SYSTEM FOR TC STORM SURGE

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The Bureau of Meteorology has recently implemented a new dynamical system to provide forecasts of storm surge driven by Tropical Cyclones (TCs). Surface forcing is derived from the Bureau of Meteorology's Official Forecast Track and its associated ensemble tracks. These are produced using the 'DeMaria' method (DeMaria et al., 2009) which takes into account historical TC track and intensity errors. Surface stress and pressure are used to force a 200-member ensemble of storm surge models, implemented using the Regional Ocean Modelling System (ROMS) model. Wave set-up and astronomical tides are linearly combined with the ROMS storm surge to provide 72-hour ensemble forecasts of coastal sea-level at a spatial resolution of approximately 2 km around the Australian coastline.

The storm surge component of the system has been described and verified for seven TC case studies using 'Best Track' forcing in Greenslade et al (2018). This presentation will provide an overview of the ensemble component of the system, including verification of the probabilistic forecasts, where possible.

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ENSEMBLE ESTIMATES OF EXTREME VALUES USING ECMWF INTEGRATED FORECAST SYSTEM

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Uncertainties in the prediction of wind and wave extremes challenge the design and construction of marine systems. Design and construction of these systems rely on accurate statistical analyses of historical data sets that provide the practitioner with Extreme Value (EV) return period estimates of environmental parameters. However, the design return periods sought stretch well beyond the length of currently available time series. Buoys, visual ship observations and platform measurements are sparse in space. The advent of satellite measurements in the last 30 years guaranteed a much better spatial coverage, but these measurements are constrained in time, due to the limited satellite record.

In response to these limitations, the present work develops an innovative approach to wind speed and significant wave height extreme value analysis. The approach is based on global atmosphere-wave model ensembles, the members of which are propagated in time from the best estimate of the initial state, with slight perturbations to the initial conditions, to estimate the uncertainties connected to model representations of reality. The low correlation of individual ensemble member forecasts at advanced lead times guarantees their independence and allows us to perform inference statistics. The advantage of ensemble probabilistic forecasts is that it is possible to synthesize an equivalent time series of duration far longer than the simulation period. This allows the use of direct inference statistics to obtain extreme value estimates. A short time series of 6 years (from 2010 to 2016) of ensemble forecasts is selected to avoid major changes to the model physics and resolution thus, ensuring stationarity. This time series is used to undertake extreme value analysis. The study estimates global wind speed and wave height return periods by selecting peaks from ensemble forecasts from +216 to +240 hours' lead time from the operational ensemble forecast data set of the European Centre for Medium-range Weather Forecasts (ECMWF). The results are compared with extreme value analyses performed on a commonly used reanalysis data set, ERA-Interim, and buoy data.

The comparison with traditional methods demonstrates the potential of this novel approach for statistical analysis of significant wave height and wind speed ocean extremes at the global scale.

BLUELINK OCEAN FORECASTING DEVELOPMENTS: OCEANMAPS, MARITIME CONTINENT AND ENSEMBLE FORECASTING

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The Bureau of Meteorology has delivered operational ocean forecasts since 2007 underpinned by the Ocean Model, Analysis and Prediction System (OceanMAPS) developed through the Bluelink research and sustainment projects. OceanMAPS version 3 is based on a near-global Modular Ocean Model version 4p1 with 1/10 x 1/10 degree resolution and 51 vertical levels which resolves a portion of the mesoscale circulation. An ensemble optimal interpolation method is applied based ENKF-C to assimilate satellite altimetry, satellite SST and in situ profiles on a 3-day cycle. Three time-lagged forecast systems provide an effective multi-cycle to provide guidance on forecast uncertainty. An overview of the current system and recent improvements will be presented including upgrading to MOM5, bulk fluxes, new observing platforms and diagnosis of forecast anomalies and their significance as shown in Figure 10.

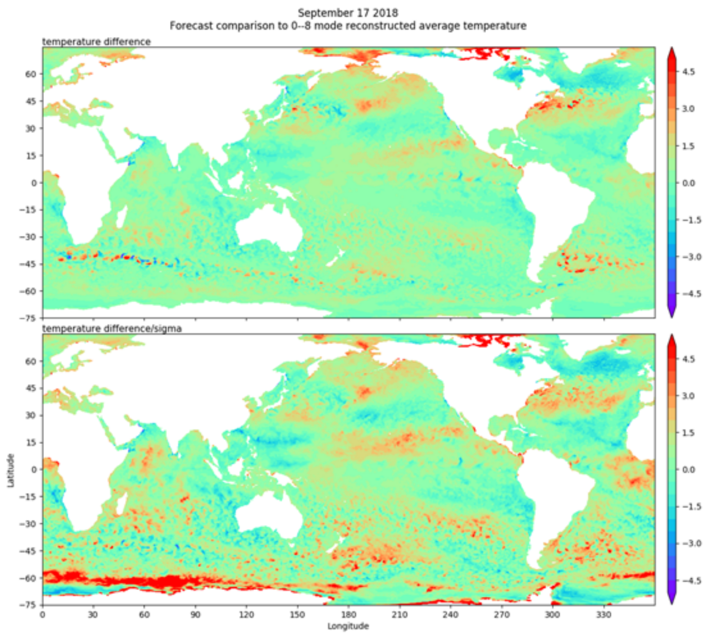

Figure 10 (upper) The OceanMAPS surface temperature anomaly for the 17 September 2018 relative to the seasonal climatology derived from BRAN, (lower) the equivalent anomaly normalied by the expected standard deviation of seasonal anomalies from BRAN.

After over a decade of development of global ocean forecasting several developments are in progress that will extend the systems capability and performance. This includes: a new fully global ocean sea-ice model being developed through an ARC linkage grant based the Modular Ocean Model version 5 with 75 vertical levels optimised for the observed variability; an updated Bluelink ocean reanalysis; and an ensemble Kalman Filter data assimilation system which provides the basis for generating probabilistic ensemble ocean forecasts. Figure 11 is a comparison of the ensemble spread of temperature at ~60 m depth based on the current OFAM3 model (left) and OFAM3 modified using the new 75 vertical levels of ACCESS-OM2-01 (right). The new vertical levels are optimized for observed ocean variability. In general the two images demonstrate comparable alignment of fronts as observed, however the new system leads to a reduction in amplitude and less diffuse indicating a reduced uncertainty.

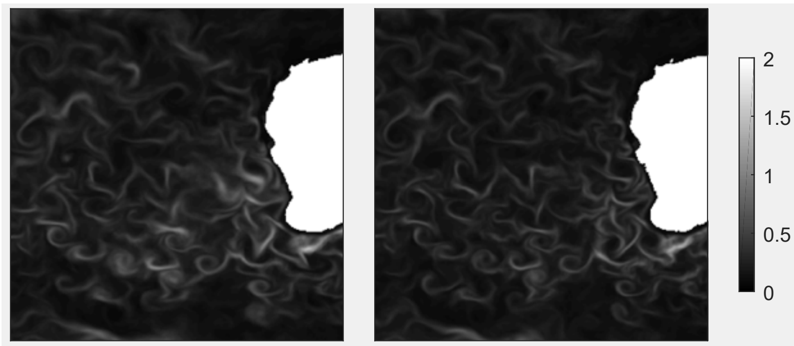

Figure 11 (left) ensemble spread of a 3 day hindcast of temperature at model level 65m. This was generated from a 96-member EnKF system based on ENKF-C applied to OFAM3. (right) ensemble spread of 3 day hindcast of temperature at model level 62 m. This was generated using an equivalent EnKF applied to the ACCESS-OM2-01 model which has 75 vertical levels. Colorbar degrees C.

Finally, we will briefly mention a new initiative to forecast the maritime continent region with a 1/50 x 1/50 degree regional downscaled ocean, wave and atmospheric model. A feature of this system is tropical cyclone and tropical lows, Indonesian throughflow, tides and internal tides within a complex archipelago. Figure 12 provides a snapshot of the tendency of the surface meridional velocity from ROMS forced by ACCESS-R fluxes. The narrow lines of peak positive and negative velocity represent an expression of an internal tidal wave which propagates and radiates from its origin.

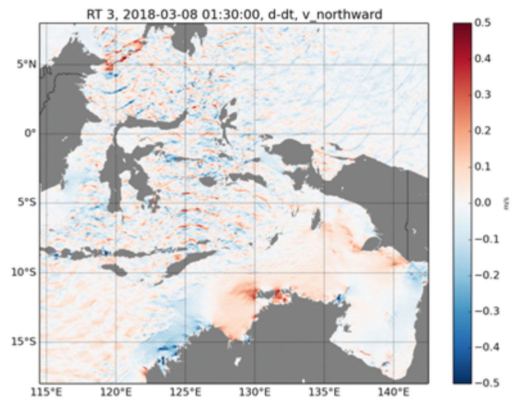

Figure 12 Tendency of meridional surface velocity from a ROMS simulation of the Maritime continent region forced by ACCESS-R atmospheric fluxes and tidal current boundary conditions.

U.S. NAVY FORECASTING DEVELOPMENTS

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Introduction

The Global Ocean Forecast System (GOFS) is the U.S. Navy's operational global ocean prediction system that runs daily at US Navy production centers. The system depicts the location of mesoscale features such as oceanic eddies and fronts, i.e. the "ocean weather", and provides accurate 3-dimensional ocean temperature, salinity, and current structure to the Fleet. The first global system was declared operational in February 2006 as GOFS 2.0 and was based on two NRL-developed ocean models, the Navy Layered Ocean Model (NLOM) and Navy Coastal Ocean Model (NCOM). Satellite altimeter data was assimilated into high horizontal resolution NLOM and its sea surface height and observed sea surface temperatures were used to create synthetic temperature and salinity profiles projected downward into the ocean interior of NCOM as part of the assimilation cycle for GOFS (Rhodes et al., 2001).

GOFS 3.0 became operational in March 2013 and represented a next generation forecast system based on the HYbrid Coordinate Ocean Model (HYCOM. GOFS 3.0 had 1/12° horizontal grid resolution, 32 layers in the vertical, an energy-loan ice capability, and used the Navy Coupled Data Assimilation System to ingest observations. HYCOM is unique in that it allows a truly general vertical coordinate, which extends the geographic range of applicability of traditional isopycnic coordinate circulation models toward shallow coastal seas and unstratified parts of the world ocean. It maintains the significant advantages of an isopycnal model in stratified regions while allowing more vertical resolution near the surface and in shallow coastal areas, hence providing a better representation of the upper ocean physics (Metzger et al., 2014).

Present/Planned GOFS Configurations

GOFS 3.1 is the present operational capability, which was declared operational on 07 November 2018 with these three new capabilities: a) increased vertical resolution (41 vs. 32 layers) to better resolve the upper ocean, b) two-way coupling between HYCOM and the Los Alamos-developed Community Ice CodE (CICE), and c) improved synthetic profile projection into the ocean interior (known as Improved Synthetic Ocean Profiles (ISOP). The higher vertical resolution in the upper ocean was designed to better represent mixed layer processes, ISOP to more accurately project surface information into the ocean interior, and CICE to provide improved physics and rheology for better sea ice concentration, thickness and drift forecasts.

The GOFS provides the Navy with a first look of the three dimensional ocean environment "anywhere, anytime" across the global ocean. These environmental fields are used to provide real time predictions of derived acoustic parameters including sound speed and sonic layer depth. In addition, the GOFS provides boundary conditions for higher resolution regional/coastal models. Ocean forecasts are also valuable for tactical planning, optimum track ship routing, asset deployment, search and rescue operations, long-range weather prediction, and the location of high current shear zones. GOFS also provides forecasts of sea ice extent and thickness in the Arctic and Antarctic. The sea ice environment in the Arctic Ocean has become increasingly important for strategic and economic reasons over the past decade given the diminishing trend in year-to-year sea ice extent and thickness and the potential summertime opening of the Northwest Passage and Siberian sea routes. Fractures, leads and polynya forecasts are also valuable to the naval submarine community.

GOFS 3.5, which is scheduled to be transitioned to operations in 2019, is similar to GOFS 3.1 except that the horizontal grid resolution is 1/25° and the system includes tidal forcing. GOFS 3.5 will provide boundary conditions for even higher resolution coastal models, and serve as the backbone of a globally relocatable ocean nowcast/forecast capability that will address the need for littoral or deep water support anywhere in the world and, at 1/25° resolution, without the need for most intermediate regional models. For the presentation, we will provide a technical description of the GOFS systems, including verification and validation as well as derived products.

Earth System Prediction Capability/Navy Earth System Model

Several U.S. agencies are coordinating a national effort to develop the future capability to meet the grand challenge of environmental predictions across a wide spectrum of space and time scales. The primary goal of the effort, known as the Earth System Prediction Capability (ESPC), is to develop and implement a fully coupled global ocean/atmosphere/wave/land/ice prediction system. The US Navy's configuration is the Navy Earth System Model (NESM). The system will provide daily deterministic high-resolution forecasts (1/25° ocean and sea ice; see Table 1) out to 16-days and lower-resolution (1/12° ocean and sea ice; see Table 1) ensemble predictions at longer lead times (45 to 60 days). Initial operational capability (IOC) is planned for the end of FY18, and Final Operational Capability (FOC) is targeted for 2022. Predictions will provide environmental information to meet Navy and DoD operations and planning needs throughout the globe from undersea to the upper atmosphere and from the tropics to the poles. The system is being implemented on Navy operational computer systems, and the necessary processing infrastructure is being put in place to provide products for Navy fleet user needs.

As the range of prediction is extended, one moves from an initial-value problem toward a boundary-value problem. The extension of the deterministic prediction from short-term 7 day forecast to mid-range time scales (~16 days) demands representing interactive physical processes in momentum, heat and mass between the earth system components that are different from the present separate systems. The exchanges between the systems need to provide representation of feedback mechanisms between components. The stand-alone Navy systems NAVGEM, HYCOM, Wave Watch III (WW3), and CICE are mature prediction systems and have considerable skill. When coupled, these models will function together as one seamless system.

As such, the coupling physics and the choice of coupling variables require special attention. In a fully coupled model, model errors propagate through the coupling interface and have nonlinear interactions. NESM has been undergoing the required testing, evaluation, validation, and improvement of the coupling physics are the necessary building blocks to develop a skillful internally consistent system. Those efforts will be summarized in the presentation.

For NESM to meet the emerging Navy/DoD extended range information dominance requirements, an ensemble approach has been implemented. Forecasts greater than ~7 days in the atmosphere and ~14 days in the ocean are limited in usefulness by inherit stochastic processes in the atmosphere and ocean. As forecast length increases, forecasts become inherently more probabilistic. The forecast products change from predicting a particular situation at a particular time, to the likelihood that a particular situation will occur over a particular time window. In addition, as forecast time increases, forecast uncertainty also increases, and a method to estimate forecast reliability becomes more important. Ensemble forecasts are a practical way of dealing with both issues. That is, if the ensembles are well-designed, they can be used to produce probabilistic forecasts (e.g., the fraction of ensemble members with winds above a certain threshold) as well as forecast reliability (e.g., large ensemble spread indicates large forecast uncertainty).

The global coupled ensemble is based on the perturb observation technique in the atmosphere, ocean, and sea ice models. Other centers have found that perturbed observation techniques do not produce adequate ensemble spread and we expect similar results in the Navy ESPC system. To deal with this issue, we will examine stochastic techniques to increases in spread. Specifically for the ocean, we are also planning to implement LETKF-based initial conditions, as well as re-centering with the (1/25°) deterministic forecast.

To date, a coupled ensemble hindcast has been integrated over 2017 with 15 ensemble members. 60-day ensemble forecasts have been performed once per week. Statistical ensemble performance metrics have been calculated and will be presented, as will ensemble means and spreads from the ocean, atmosphere, and sea ice.

Forecast	Time Scale, Frequency	Atmosphere NAVGEM	Ocean HYCOM	Sea Ice CICE	Waves WW3[1]	Land Surface LSM	Aerosol[2]
Deterministic	0-16 days daily	T681L60 (19 km) 60 levels	1/25° (4.5 km)[3] 41 layers	1/25° (1.8 km)[4]	1/8° (14 km)	Module within NAVGEM	Offline outside NAVGEM
Probabilistic (Ensemble)	0-45 days once a week 15 members[5]	T359L60 (37 km) 60 levels	1/12° (9 km)[3] 41 layers	1/12° (3.5 km)[4]	1/4° (28 km)	Module within NAVGEM	Offline outside NAVGEM

Table 1. Horizontal and vertical resolutions of the individual ESPC components at Initial Operational Capability (IOC). [1] One-way coupling of atmosphere-ocean-sea ice to WW3. [2] One-way coupling of atmosphere to aerosol. [3] Horizontal resolution at the equator. [4] Horizontal resolution at the North Pole. [5] The exact number of members will be determined by the operational resources available.

ENSEMBLE ESTIMATES OF FUTURE CLIMATE FROM THE COWCLIP DATASET

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Multiple coupled interactions characterize the atmosphere and the oceans driving many aspects of geophysical processes, and ultimately affecting the climate. Understanding potential changes in wind wave extremes is of paramount importance to assess future potential impacts on coastlines, marine operations and construction. A climate change signal has been thoroughly demonstrated in the mean values of surface winds and wind waves, but a reliable analysis of changes in the extremes is still missing.

Extreme Value Analyses (EVA) are commonly used for long-term estimates of extreme ocean storms, however the climate is usually considered stationary. Furthermore, common statistical approaches are uncertain due to short and inhomogeneous time series. Models are incapable of accurately representing extreme events, and wind and wave observations that are used to calibrate the models, are often biased at the extremes. Therefore, these uncertainties hinder a robust evaluation of long term return periods, with low confidence in the results.

The present work deals with these uncertainties, applying an innovative ensemble technique for the EVA of significant wave height (SWH) 100 year return period differences between the historical (1979-2005), and the end of the 21st Century (2081-2100) climates. The dataset consists of an ensemble of global wave model -WAVEWATCH III- SWH. These are outputs of the wave model forced with 7 different Global Climate Model surface wind fields from the Climate Model Intercomparison Project phase 5 (CMIP5). The inter-model independence and identical distribution of the extremes allow common statistical approaches. Thus, the SWH highest peaks are pooled from the 7-model ensemble and the resulting data series is representative of a time interval larger than the return period sought, strongly increasing confidence levels in the estimates.

An ensemble Peak Over Threshold (ensPOT) approach and an ensemble Annual Maxima approach (ensAM) have been applied. The RCP8.5 high emission scenario (CMIP5), shows similar trends in the SWH for extended areas of the oceans, with a distributed increase of wave height extremes particularly in the Southern Ocean, arguably related to an increase in frequency of the extreme events. The regions of the global oceans affected by local climate variability -such as Tropical Cyclones-, still present high uncertainty due to model incapability of representing these phenomena at current resolution. However, the constant improvement of global models and their progressively finer resolution will further increase the level of confidence using this approach.

BIAS-CORRECTION OF TROPICAL CYCLONE STRUCTURE IN ECMWF ENSEMBLE PREDICTION SYSTEM FOR NW AUSTRALIA

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This paper describes the application of statistical techniques for the purpose of correcting systematic biases in global ensemble tropical cyclone (TC) predictions. The study aims to improve model predictions for tropical cyclone events provided by Numerical Weather Prediction models. The region of focus is the Northwest Shelf of Western Australia, which is a highly active region for tropical cyclone genesis in the Australian region. The region is characterised by a large number of oil and gas assets that are particularly vulnerable to the effects of TCs. Better TC genesis forecasts will improve the ability of the oil and gas industry to plan for cyclones that are in the process of forming.

We have developed methods to correct the biases in the European Centre for Medium-Range Weather Forecast Ensemble Prediction System (ECMWF EPS) that mainly arise due to its relatively coarse resolution. We employ three different statistical techniques for bias correction: 1) Simple Linear Regression; 2) Multivariate Regression; 3) Principal Component Analysis (PCA). We use the Australian best track data for verification. A comparison of root-mean-square-errors (RMSE) resulting from the three methods shows that the PCA generally performs better than the simple and multivariate regression models.

The IKE was found to be a valuable predictor in all three models. We found that the EPS Rmax was not well-correlated with the best-track Rmax. The relatively poor performance of Rmax was expected, as most models have little ability to predict it and very high resolution is needed to avoid systematic biases. After bias-correction, we verify the predicted parameters using the spread-skill relationships and rank histograms. We then replace the model surface fields with a bias-corrected vortex using a modified Rankin vortex. These adjusted wind fields provide better-calibrated wind exceedance probability guidance than the raw model output, and are used to force a wave model and generate better-calibrated wave probabilities.

WAVE ENSEMBLE FORECAST SYSTEM FOR TROPICAL CYCLONES IN THE AUSTRALIAN REGION

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Wave forecasts for North West Western Australia (NW WA) issued by the Bureau of Meteorology have previously been limited to products from deterministic operational wave models forced by deterministic atmospheric models. The wave models are run over global (resolution 27.5km) and regional (resolution 12km) domains with forecast ranges of 168h and 72h respectively. Because of this relatively coarse resolution (both in the wave models and in the forcing fields), the accuracy of these products is limited under tropical cyclone (TC) conditions.

Given this limited accuracy, we have developed a new ensemble-based wave forecasting system for the NW WA region. To achieve this, a new dedicated 8-km grid was nested in the global wave model. Over this grid, the wave model is forced with winds from a bias-corrected ECMWF atmospheric ensemble (240h lead time) that comprises 51 ensemble members to take into account the uncertainties in location, intensity and structure of a tropical cyclone system. The system is designed to operate in real time during the cyclone season. This presentation will outline the system, describe some of the main issues encountered and present the verification of specific events.

THE EREEFS OPERATIONAL COASTAL OCEAN PREDICTION SYSTEM OF THE BUREAU OF METEOROLOGY

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The Bureau of Meteorology developed an operational ocean prediction system over the 2014-2017 period. As part of the development state of the art 10 year reanalyses of the Great Barrier Reef (GBR) and a 2 year long high resolution hindcast dataset have been developed. Currently a routine real-time ocean forecast of the GBR is available to the Australian Community every 6 hours. The system attempts to provide the best estimate of the physical system with a particular focus on freshwater fluxes and passive tracers. This has been achieved by implementing a state of the art Ensemble Optimum Interpolation (EnOI) data assimilation system. The products are available via internet data servers and graphical web-viewers. Here we will report on the design and performance of the eReefs prediction system and further comment on potential future developments in the area such as test beds for using a non-stationary ensemble i.e. moving towards an Ensemble Kalman Filter (EnKF) system.

ENSEMBLE OPTIMAL INTERPOLATION SST ANALYSIS SYSTEM BASED ON THE ENKF-C SYSTEM

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Abstract

A new experimental global, Sea Surface Temperature (SST) analysis system ("GSAS") is presented, based on public, Ensemble Kalman Filter data assimilation C code (EnKF-C; Sakov, 2018) developed by the Bureau of Meteorology (BoM) under the Bluelink Project. The GSAS system uses the Ensemble Optimal Interpolation (EnOI) method. It uses the previous analysis as the background field, and implicitly calculates covariances from a static ensemble of SST fields, based on the operational ocean forecasting system OceanMAPS. The system covers the region 75°S to 75°N and produces daily foundation SST analyses on a 0.1° x 0.1° rectangular grid, by assimilating global infrared and microwave satellite SST data streams from Suomi-NPP, GCOM-W, METOP-A/B and NOAA-18/19 polar-orbiting satellites.

The advantages of using the EnOI GSAS system for SST analysis will be outlined, including anisotropic covariance, computational efficiency, use of superobservations to handle different resolution input products, and the ability to account for observation error. Comparisons will be shown between GSAS and the BoM and Canadian Meteorological Centre (CMC) operational daily, optimal interpolation SST analyses.

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ENSEMBLES IN THE OCEAN: AN ECMWF PERSPECTIVE

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Introduction

This presentation reviews different approaches explored for ensemble generation for initialization of seasonal forecast. It then focuses on describing the approach used at ECMWF for creating ocean perturbations in the current ocean reanalysis. It concludes by illustrating the impact of coupled data assimilation in the ensemble spread of surface fluxes.

The ECMWF scheme for ensemble generation in the ocean

A new generic perturbation scheme suitable for generation of an ensemble of ocean analysis has been developed at ECMWF (Zuo et al 2017). The scheme consists of two distinct elements: perturbations to the assimilated observations, both profiles and surface observations, and perturbations to the surface forcing fields. The new scheme has been applied to the new Ocean ReAnalysis System-5 (ORAS5, Zuo et al 2018). The surface forcing perturbation has also been used to create oceanic surface forcing for ERA5, and in operational Ensemble Data Assimilation (EDA) from cycle 43R1.

The idea behind the observation perturbation scheme is to account for observation representativeness error. Instead of perturbing the value of the assimilated observations, the scheme perturbs the position of the observations. This is done by applying perturbations to the geographical location of the *in-situ* temperature and salinity profiles, and by random thinning, both in the horizontal for surface observations, and in the vertical for dense profiles. This method exploits the full observation data set and uses more observations (through ensemble approach) than the previous thinning method. The impact of the perturbation scheme in the ocean reanalysis is illustrated together with selected sensitivity experiments. It is shown that the observation perturbations have little impact in global or basin wide climate indices, but they have local effect. The ensemble spread shows large errors in regions with strong mesoscale eddy activities and in areas affected by the Mediterranean Outflow waters. These are regions where departures with respect to observations are also large. It is also shown that ensemble spread in the tropical upper-ocean is under-dispersive with only five ensemble members, but it improves by increasing the ensemble size.

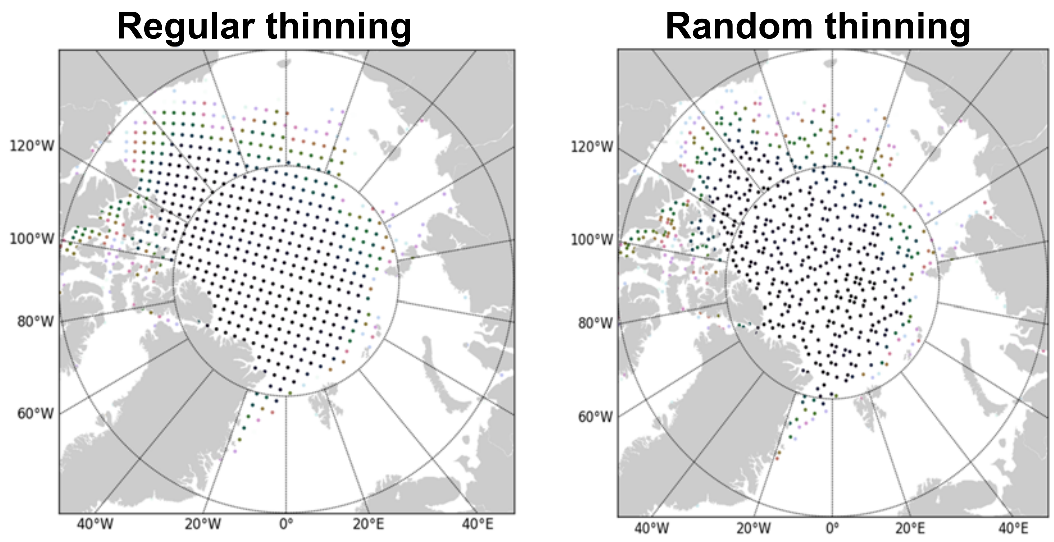

Figure 1: Daily averaged gridded sea-ice concentration data from OSTIA as assimilated in (left) the control member with regular thinning; and in (right) a perturbed member using stratified random sampling method. Here thinning box length-scale is approximately 100 km in the Arctic Ocean.

A revised scheme for generating perturbations to surface forcing has also been developed. It is a generalization of the previous scheme and is still based on sampling past differences between different sources of information. The previous scheme, implemented as part of the seasonal forecasting system 2 (S2), created monthly perturbations for wind stress and Sea Surface Temperature (SST), based on sampled differences between atmospheric re-analysis products. The new scheme is more general in several aspects: i) it allows for representation of both analysis and structural uncertainty; ii) it permits different temporal de-correlation scales of the perturbations; iii) it encompasses a wider range of variables and iv) it preserves the multivariate relationships among the perturbed variables. The reference data sets for sampling the perturbations have also been updated. The analysis uncertainty is sampled using the ensemble information from ERA-20C. The structural uncertainty in SST is sampled using more up-to-date data sets of high resolution ESA-CCI and HadISSTv2.1. Sea Ice Concentration (SIC) structural uncertainty is sampled using differences between HadISSTv2.0 and v2.1. The scheme is not fully flow dependent yet as it represents only the seasonal variations of uncertainty. However, it has been designed to be compatible with the flow dependent perturbations such as those produced by the real-time EDA; in particular, the climatological analysis uncertainty perturbations can be replaced by those from the EDA when the latter becomes available. The new SST and sea-ice perturbation strategy developed is also used by ERA5 and by the operational EDA (albeit with different parameter choices).

Impact of coupled data assimilation in flow dependent ensemble spread

The impact of coupled data assimilation in the flow dependence of the ensemble spread is assessed by comparing the time evolution of the spread in two different systems. The first one is ORA-20C (De Boisseson et al 2017), a 10-member ensemble of uncoupled centenial ocean reanalyses, and the recently developed CERA-20C (Lolayaux et al 2018), a 10-member ensemble of coupled ocean-atmosphere-seaice-wave-land reanalysis covering the XX century. ORA-20C uses the ensemble generation approach described above, which has limitations on the representation of the flow dependent spread. Figure 2 shows the ensemble spread in absorbed solar radiation as prescribed in ORA-20C, and the one resulting from the coupled reanalysis CERA-20C. The figure shows that the coupled reanalyses represents the decadal variations in the uncertainty of the forcing fluxes, with large uncertainty in the early decades of the XX-Century.

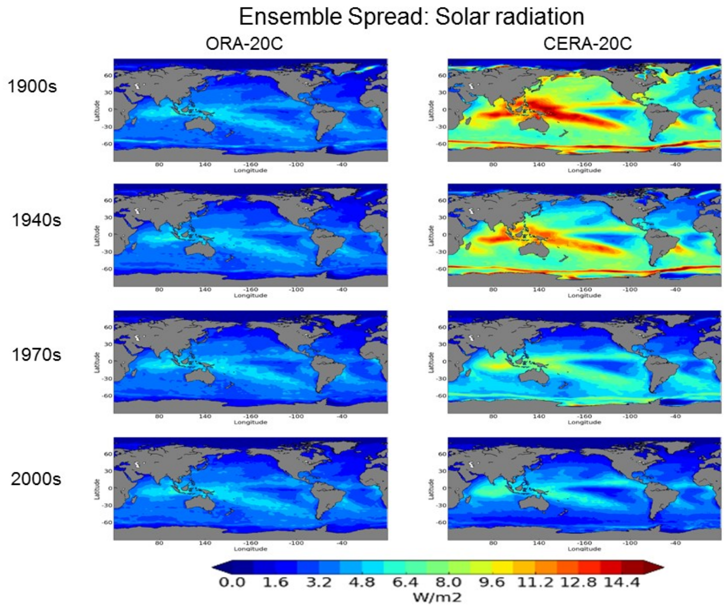

Figure 2: Decadal variations of the spread in solar absorbed solar radiation (left) in the ORA-20C 10-member ensemble of uncoupled reanalysis (De Boisdeson et al 2017) and (right) in the 10-member ensemble of coupled reanalysis (Laloyaux et al 2018). The larger uncertainty in the earlier decades of the XX-century is better captured in the coupled reanalyses.

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COUPLED DATA ASSIMILATION AND ENSEMBLE INITIALISATION WITH APPLICATION TO MULTI-YEAR ENSO PREDICTION

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We develop and compare variants of coupled data assimilation (DA) systems based on ensemble optimal interpolation (EnOI) and ensemble transform Kalman filter (ETKF) methods. The assimilation system is first tested on a small paradigm model of the coupled tropical-extratropical climate system, then implemented for a coupled general circulation model (GCM). Strongly coupled DA was employed to perform an observing system simulation experiment (OSSE) and to assess the impact of assimilating ocean observations (SST, SSH, SSS, Argo, XBT, CTD, moorings) on the atmospheric state analysis update via the cross-domain error covariances from the coupled-model background ensemble. We examine the relationship between ensemble spread, analysis increments and forecast skill in multi-year ENSO prediction experiments with a particular focus on the atmospheric response to tropical ocean perturbations. Initial forecast perturbations generated from bred vectors (BV) project onto disturbances at and below the thermocline with similar structures to ETKF perturbations. BV error growth leads ENSO SST phasing by 6 months whereupon the dominant mechanism communicating tropical ocean variability to the extra-tropical atmosphere is via tropical convection modulating the Hadley circulation. We find that bred vectors specific to tropical Pacific thermocline variability were effective choices for ensemble initialization and ENSO forecasting.

We first consider a paradigm model of tropical - extratropical interactions. In this small 9D model, three versions of the famous Lorenz 63 model are coupled to mimic the temporal behavior of an extratropical atmosphere weakly coupled to a tropical atmosphere which in turn is strongly coupled to a slow tropical ocean. We compare EnOI and ETKF data assimilation where only "ocean" observations are assimilated but cross-domain covariances are included between all state variables. These simulations point to the potential for a well constrained ocean state to also constrain the tropical atmosphere, in large part due to the strong coupling between ocean and tropical atmosphere. Here, and in the context of the paradigm model, well constrained requires that flow dependent information be captured in the ocean-tropical atmosphere cross covariance. While flow dependent information constrains the ocean - tropical atmosphere, despite being weakly coupled, cross covariance information between the ocean, tropical and the extra-tropical atmosphere attractors led to a suppression of the variance in the analyzed extra-tropics. In contrast, where static rather than flow dependent cross covariances are employed, the analyzed tropical atmospheric state, despite being strongly coupled to the ocean attractor, fails to track the truth, but the variance of the analyzed extra-tropical attractor was largely unchanged even with increments due to the cross covariance included. These simple model experiments suggest that one might best initialize ensemble climate forecasts by constraining the slow modes of the ocean with only a relatively weak large scale projection of ocean observations into the fast extratropical atmospheric circulation. It is on this basis that we then examined strongly coupled DA variants applied to the GCM, where the ocean is constrained, either with static or flow dependent cross covariances, and where the large scales of the atmosphere are modified based on suitably scaled ocean-atmosphere cross covariances.

Our focus is on seasonal and longer timescales, and in particular ENSO. Therefore, our premise underpinning the OSSE's is that predictability primarily resides in the oceans and the fast atmosphere acts as a stochastic driver on the longer timescale ocean variability. We again considered two approaches to DA based on ETKF and EnOI, assimilating a wide range of ocean observations into a GCM. Outside of the tropics the ETKF system produced dramatically lower forecast bias and forecast mean absolute deviations (MAD) relative to the EnOI system however, these improvements were substantially reduced in the tropics. The reason for the low analysis error in the EnOI system in the tropics was found to be a result of seasonally dependent fixed ensemble spread at times producing larger observation impacts relative to the tropical ETKF where interannual variations in the background covariances can lead to periods of relatively reduced spread.

Initial forecast perturbations using bred vectors (BV's) representative of growing coupled tropical instabilities were found to modify tropical convection, particularly in the region of the maritime continent, which in turn generate a coherent modulation of the Hadley circulation. A direct renormalization of thermocline disturbances was found to be most effective in communicating information from the tropical ocean to the extra-tropical atmosphere on timescales of a couple of weeks to a month. Comparison of ensemble forecasts based on two types of bred vectors (masked and unmasked) centered about the EnOI analyzed state reveal a substantial reduction in uncertainties (forecast spread), when disturbances not directly associated with thermocline variability are eliminated. In particular, excluding SST disturbances led to a significant reduction in forecast errors in multi-year ENSO predictions and noticeably increased skill at lead-times out to two years. These results affirm the utility of using BV's explicitly constructed to project onto forecast errors entirely due to tropical subsurface ocean disturbances where the appropriate variance resides in application to ENSO prediction.

The OSSEs and methods discussed form a basis for coupled DA relevant to multi-year near term climate forecasts. The masked isosurface BV approach allows for the specific targeting of regions of large scale variability pertinent to dynamical processes that determine predictability on seasonal to interannual spatio-temporal scales. Beyond a season, strongly coupled data assimilation, where the slow ocean modes are explicitly constrained including projection onto the background atmospheric states (i.e. jets, cells etc) while leaving the fast atmospheric dynamics (synoptic scales) free, including targeted forecast perturbations, offers a pragmatic approach to determining the mechanisms and predictability of the key climate modes.

This work further highlights the complexity of data assimilation and forecast initialization in nonlinear multiscale systems. While we have demonstrated the advantages of flow dependent ocean data assimilation and the usefulness of ocean observations to constrain the large scales of the atmosphere, it is apparent that assimilation of atmospheric observations is further required to guarantee the correct extratropical variability. This is a focus of our ongoing work, as are methods to identify an appropriate theoretical basis necessary for identifying causal relationships between climate modes and for determining predictability on given spatio-temporal scales of interest and as a basis for developing a generalizable approach to multiscale forecast initialization.

ENSEMBLE FORECAST PRODUCTS FOR USER DECISIONS ON MULTI-WEEK TO SEASONAL TIMESCALES

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Ensemble-based forecasts are the bread and butter of probabilistic multi-week and seasonal outlooks. While many of us know what kinds of products our research could ultimately produce, the question of *why* we produce them is sometimes not front of mind. The "why" is ultimately to help decision makers in weather and climate sensitive sectors make better choices. No matter how accurate a weather forecast or climate outlook is, if it does not provide the information users need, if it is not issued when users are making their critical decisions, if it is misinterpreted and if it cannot help make a decision – then the forecast has little real value.

A newly funded multi-institution 5-year project will deliver direct value to the agricultural sector through providing forecasts of extremes and equipping farmers with the information and tools to be forewarned and prepared. The project is supported by funding from the Australian Government Department of Agriculture and Water Resources as part of its Rural R&D for Profit programme. The Bureau of Meteorology (BoM), working with a number of research partners, will develop and deliver ensemble forecast products of the likelihood of climate extremes on multi-week to seasonal timescales – beyond the 7-day weather forecast. This will provide farmers with the first ever forecasts of extremes weeks to seasons ahead. The forecasts will be based on BoM's seasonal forecast system, ACCESS-S. The BoM component of the project includes research to 1) evaluate user needs, 2) understand large-scale drivers (e.g., El Niño, the MJO) of extremes, 3) improve ACCESS-S to give better forecasts of extremes, and 4) develop experimental forecast products which will be trialed by users to assess value. A subset of products that have sufficient accuracy and utility will be delivered as official BoM forecasts to the benefit of agriculture. Project partners who are agricultural climate and systems analysis researchers, with particular expertise in the dairy, beef, sheep, grains, sugar and wine industries, will use BoM output to determine climate extremes scenarios through appropriate risk management frameworks, farm system models and economic frameworks.

We will present the plan and scope of the project, as well as the first set of ensemble forecast products that will be trialed with project partners and stakeholders.

ACCESS-S1 OCEAN FORECAST PRODUCTS FOR MARINE INDUSTRY APPLICATIONS IN NEW ZEALAND

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A joint initiative is underway between the Australian Bureau of Meteorology (BoM) and the National Institute of Water and Atmospheric Research (NIWA) in New Zealand to develop multi-week and seasonal ocean forecast products for aquaculture in New Zealand using the Bureau's new seasonal prediction system ACCESS-S1.

ACCESS-S1 has significantly improved horizontal (25km vs 100-200km) and vertical (1m vs 15m for upper layers) grid spacing in the ocean compared to its predecessor POAMA, which permits the resolution of finer features, particularly in coastal areas and for upper-level sea temperature forecasts. This opens up exciting new opportunities for the development of localised forecast products which would have been unfeasible on the coarser POAMA grid.

Fisheries and aquaculture are significant industries in New Zealand (worth ~NZ$1.4B). These industries are sensitive to marine heat waves such as the 2017/18 heat wave, so would benefit from advance warning of extreme events through forecasts of relevant parameters such as Sea Surface Temperature (SST) and Heat Content (HC).

An assessment of the SST and 300m HC ensemble mean and probabilistic forecast skill of ACCESS-S1 has been undertaken using a set of retrospective ensemble forecasts for 1990-2012, verified against Reynolds AVHRR satellite observations and the Bluelink ReANalysis 3.5 (BRAN3.5) dataset. A set of trial realtime forecast products is now being developed, with a focus on Hauraki Gulf, Cook Strait, and Stewart Island – three areas key to the aquaculture and fisheries sectors. These products include SST ensemble mean anomaly and full field maps, as well as probabilistic forecasts such as the probability of a given week or month falling into the top tercile or quintile of the hindcast period.

The improved resolution of ACCESS-S1 provides an opportunity to forecast SST for localised regions around New Zealand, and we have shown that the model demonstrates promising skill in these regions. This will provide a beneficial source of guidance for routine operations. Furthermore, the ability of ACCESS-S1 to signal the onset extreme events such as marine heatwaves will make it a valuable tool for reducing economic loss.

ENSEMBLE MJO PREDICTION WITH ACCESS-S1

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The Bureau of Meteorology has developed a new dynamical seasonal forecasting system, the Australian Community Climate and Earth-System Simulator (ACCESS-S1). One of the main targets of our research is to improve subseasonal prediction skill of the Madden-Julian Oscillation (MJO) and its impacts on Australian and global climate. Improving the depiction and prediction of the MJO serves to provide improved prediction of tropical and extratropical climate patterns, tropical storms and cyclones, monsoons, and global ocean surface waves. While climate models currently achieve ensemble-mean prediction skill for the MJO at lead times ranging from about two to four weeks, global teleconnections driven by the MJO are often too weak, particularly for the lower-resolution models, and thus there exists great potential for further improving our prediction of MJO impacts.

We assess the ability of ACCESS-S1 to predict the MJO using retrospective ensemble forecasts for the period 1990-2012. The ACCESS-S1 hindcast ensemble uses 11 members from 4 start dates per month. Initial perturbations are introduced only in the atmospheric initial conditions through a modified version of random field perturbations. In contrast, the POAMA-2 system uses a method of coupled breeding that generates coupled ocean and atmosphere perturbations. Nonetheless, ACCESS-S1 demonstrates improved skill in predicting the bivariate Real-time Multivariate MJO (RMM) index by about 4 days lead time in austral summer and 5 days in boreal summer compared to POAMA2. Probabilistic forecast scores further demonstrate improved skill in predicting MJO amplitude by at least 7 days, and MJO phase by about 9 days. However, the ensemble from ACCESS-S1 for the MJO is underdispersed, indicating further gains in forecast skill can still be achieved when the ensemble perturbation method is upgraded in the future.

Recent work has shown the MJO to be significantly modulated by the stratospheric Quasi-Biennial Oscillation (QBO). The MJO during boreal winter is observed to be stronger during the easterly phase of the QBO than during the westerly phase, with the QBO zonal wind at 50 hPa leading enhanced MJO activity by about one month. Using retrospective forecasts from both POAMA-2 and ACCESS-S1, we show that this strengthened MJO activity during the easterly QBO (EQBO) phase translates to improved prediction of the MJO and its convective anomalies across the tropical Indo-Pacific region by about 8 days lead time relative to that during westerly QBO (WQBO) phases. All operational models participating in the WCRP/WWRP Subseasonal-to-Seasonal (S2S) prediction project also show a higher MJO prediction skill during EQBO winters than during WQBO winters, with enhanced MJO prediction skill of up to 10 days. These improvements in forecast skill result not just from the fact that forecasts are initialized with stronger MJO events during EQBO, but also from the more persistent behaviour of the MJO for a similar initial amplitude during QBO easterly phases as compared to QBO westerly phases. The QBO is thus an untapped source of subseasonal predictability that can provide a window of opportunity for improved prediction of global climate.

Finally, we describe a new approach for presenting probabilistic forecasts of the MJO based on the RMM index. This new display overcomes the difficulty of interpreting a dispersive ensemble plume and directly quantifies the probability for the MJO to occur in each of its eight RMM-defined phases as well as the weak phase. This innovative method for accessing probability of the state of the MJO in an ensemble forecast compliments the traditional MJO ensemble forecast display and verification and will benefit global forecasting centres, international MJO working groups, and the S2S project.

STOCHASTIC PARAMETRISATION

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Fundamental reasons for treating as stochastic computational representations of the underlying differential equations for weather and climate are discussed. The impact of SPPT and Stochastic Backscatter on forecast skill and systematic error are reviewed – focusing on the seasonal timescale. Emphasis is placed on the role of stochasticity as a “poor-man’s” alternative to enhanced resolution is discussed, especially for improving the representation of persistent weather regimes. The role of stochasticity in designing computationally efficient next-generation weather and climate models will be described.

SUMMARY OF POAMA OPERATIONAL CLIMATE FORECAST SERVICES OF AUSTRALIAN BUREAU OF METEOROLOGY: 2013-2018

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Abstract

Since 2013 the Australian Bureau of Meteorology's National Climate Centre (NCC) has upgraded its operational climate outlook services from statistic based system to a dynamic model named Predictive Ocean and Atmosphere Model for Australia (POAMA) based. Development and application of this first dynamic model based forecast system with potential forecast capability being investigated to support the designing of the so called lagged ensemble approach. It was also found that POAMA is especially skilful over the most populated coastal areas of the country. By use of the so called confident forecasts, the reliability and accuracy of the services could be further improved.

After about 6 years of services, in 2018, POAMA was replaced by the more advanced model called Australian Community Climate and Earth System Simulator for seasonal prediction (ACCESS-S). In order to improve the dynamic model based climate outlook practice, the performance of POAMA has been investigated. Using same verification metrics, performance of POAMA's real-time forecasts were compared with its potential skills estimated from its hindcast analysis showing that real-time forecasts actually outperformed the hindcast in general. Being aware of the skill differences between real-time and hindcast, it was also argued that hindcast assessment should mainly be used to conclude whether the model has reliable and significant skill or not, in order to justify the application of a model. In other words, users should not over-interpret hindcast skill as it has inevitable uncertainties caused by all sorts of reasons, hence actual skill may change from one forecast to another and from one event to another. Some typical successful or failed forecasts were discussed in more details to assess POAMA's real-time performance.

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USING CLIMATE PROJECTIONS TO UNDERSTAND IMPACTS AND INFORM AGRICULTURAL ADAPTATION

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Introduction

Climate change is already impacting agriculture in Australia, with recent studies quantifying these impacts in wheat production (Hochman et al. 2017; Taylor et al. 2018), wine grapes (Webb et al. 2012) and grazing (Cullen et al. 2009). For agriculture to adapt to climate change, each industry will require regionally specific information about the likely future rainfall patterns and temperature changes, to enable their farm systems models to predict the likely impacts. These impacts can include earlier ripening of grapes (Webb et al. 2012), declining in wheat yields (Hochman et al. 2017), a greater frequency of crop failure (Taylor et al. 2018), or changes in the seasonal growth rate patterns in pastures (Cullen et al. 2009).

A common approach to understanding climate change impacts is to use Global Circulation Model (GCM) data to scale historical climate data to create the regionally specific future daily climate libraries required to drive crop and pasture system models. There are numerous variations on how this can be achieved, from simple arithmetic scaling, through to complex statistical techniques. This paper discusses three case studies by the authors, illustrating how the data then informs adaptation within each industry.

Climate change effects on pasture systems in south-eastern Australia

The effects of future climate scenarios on pasture production were modelled at 5 sites in eastern Australia, ranging from a C4-dominant pasture in subtropical south-eastern Queensland to a C3 pasture in the cool temperate environment of north western Tasmania (Cullen et al. 2009). A 30-year climate ‘baseline’ (1971–2000) was used to represent inherent climate variability at each site, based on data from the SILO database (Jeffrey et al. 2001). Future climate scenarios were developed, by adjusting baseline climate data with climate change projections for 2030 and 2070, based on the A1FI and A1B emission scenarios with both medium and high climate sensitivity, to create 30-year realisations of each future climate scenario. Monthly projections for mean temperature (ºC) and rainfall (%) change were obtained from the CSIRO Mark 3 global circulation model, via the OzClim database. These monthly change factors were used to mathematically scale the historical data for each site. The historical data was not detrended as there were no significant linear annual trends over the 30-year record.

The resultant daily climate libraries were then used to drive the SGS and DairyMod pasture models (Johnson et al. 2003; Johnson et al. 2008) to simulate rainfed pasture growth (e.g. Figure 1) for each site, for the baseline period, and then for 30 potential realisations of a 2030 and 2070 year.

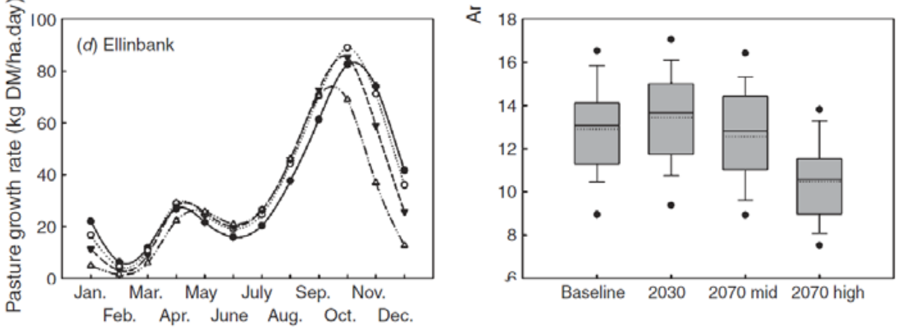

Figure 1. Mean monthly predicted pasture growth rate (kg DM/ha.day) for baseline (solid line), 2030 (dotted), 2070 mid (dashed), and 2070 high (mixed) climate scenarios, together with box-plots of predicted annual production (t DM/ha) for the baseline, 2030, 2070 mid, and 2070 high climate scenarios at Ellinbank in West Gippsland, Victoria.

More recently, Harrison et al. (2016) compared the impact of simple monthly scaling (Gradual) with a 'Variable' approach which incorporated projections for extreme climate events; for example, with rainfall occurring in fewer, larger events. The 'Variable' approach consistently simulated lower pasture production than the 'Gradual' approach (Figure 2) even though the monthly average rainfall and temperatures were held constant. These findings highlighted the importance of incorporating projections for increased climatic variability and extreme climate events into future scenarios.

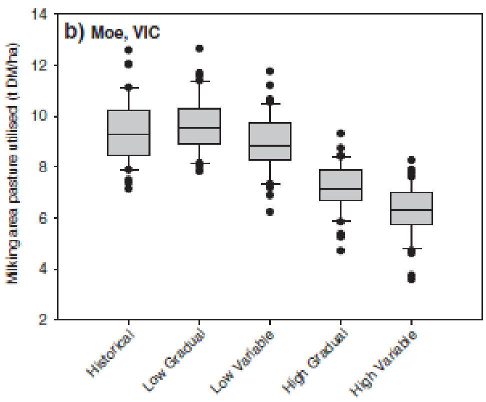

Figure 2. Boxplots of annual pasture utilised (t DM/ha) on a case study farm in Moe, Gippsland Victoria, under an historical climate (1975-2013), and Low and High change projections for 2080 using the 'Gradual' and 'Variable' approaches.

Potential impacts of climate change on soil organic carbon and productivity in pastures of south eastern Australia

Meyer et al. (2018) modelled the potential impact of climate change on soil organic carbon under grazed pasture systems at two sites in western Victoria. The methodology for developing the downscaled future climate file built on that of Cullen et al. (2009). Climate change factors were obtained from SimCLIM 2013 AR5 software (version 2.1) (Warrick 2007). All 40 of the GCMs from the coupled model inter-comparison (CMIP 5) available in SimCLIM were included in the ensemble used to generate the climate projections. The GCMs that produced the 10th, 50th and 90th percentile temperature (GCMt) and rainfall (GCMr) projections were used to develop five future climate scenarios, for both the 4.5 and 8.5 Representative Concentration Pathways (RCPs): hot and dry (90th percentile GCMt90 and 10th percentile GCMr10); warm and dry (10th percentile GCMt10 and GCMr10); intermediate (50th percentile GCMt and GCMr); hot and wet (90th percentile GCMt90 and GCMr90), and warm and wet (GCMt10 and GCMr90). Climate libraries from 2017 to 2090 were generated by applying change factors to the historic SILO patch point dataset, detrended for historic climate change effects on temperature. For each climate variable there were different change factors for the 3 selected climate models (10th, 50th and 90th percentile GCM), 2 emissions scenarios (4.5 RCP and 8.5 RCP), 2 seasons (winter growing season and summer) and 2 sites (high rainfall at Hamilton and low rainfall at Birchip).

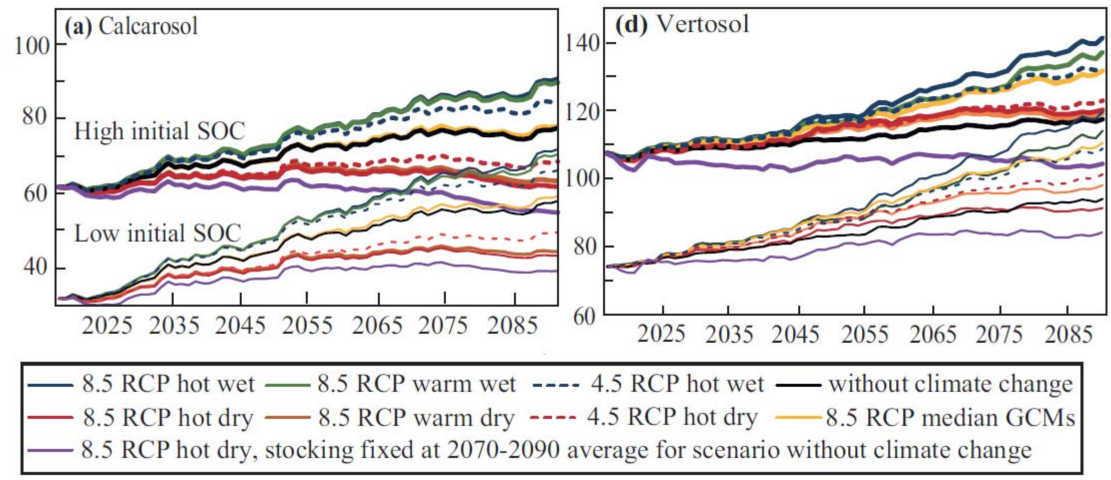

Figure 3. Modelled change in SOC from 2017 to 2090, for low and high initial SOC over several climate and 2 soil type scenarios.

The resultant daily climate files were then used to drive the SGS pasture model (Johnson et al. 2003; Johnson et al. 2008), with the SGS model also providing inputs into the Roth C soil carbon model. The models where then run from 2017 through to 2090, for two soil types at each site, each starting with either low or high soil organic matter, to show potential interactions between stocking rate and soil carbon under a changing climate (e.g. Figure 3).

Trends in wheat yields under representative climate futures: Implications for climate adaptation

Taylor et al. (2018) modelled the potential impact of climate change on wheat yield across southern Australia. The methodology for developing the downscaled future climate libraries built on the approaches of Cullen et al. (2009) and Meyer et al. (2018). A set of Representative Climate Futures (RCF) (Whetton et al. 2012) was developed, based on RCP4.5 and RCP8.5, to describe plausible future climate scenarios, based on data from Climate Change in Australia. The full suite of available GCMs was used and individual GCMs were organised into: a) the 'most likely' case, defined as at least 30% or more of total number of GCMs in agreement, b) the 'best' case, defined as the climate future resulting in the highest rainfall and lowest temperature increase, and c) the 'worst' case, defined as the lowest rainfall and highest temperature increase (Whetton et al. 2012). The GCMs were ranked using a multivariate ordering technique (Kokic et al. 2002). The GCM closest to the multi-model mean of the 'most likely' case was selected, along with the GCMs aligning with the minimum and maximum being selected for the 'best' and 'worst' cases, respectively. The resultant change factors were then applied to the historical SILO data for each site as per Cullen et al. (2009), for a 31-year baseline period from 1980 to 2010, with 1995 as the centred year to predict wheat yields using APSIM (Figure 4).

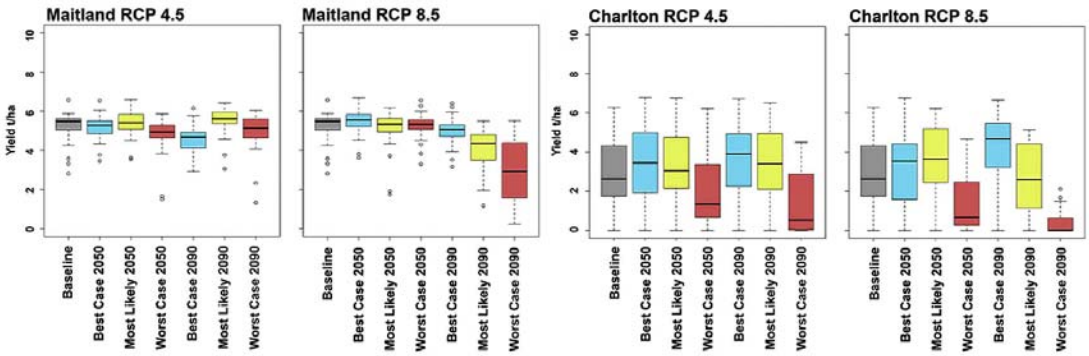

Figure 4. Box and whisker plots of projected changes to wheat yield on selected study sites. The grey box represents the baseline climate 1980 to 2010. The blue, yellow and red boxes represent the low (best case), mean (most likely) and high (worst) climate change cases, respectively.

Informing agricultural adaptation

The three case studies above have been used to inform both industry and government policy and identify further research on adaptation to the changing climate.

The pasture case study identified changes to seasonal pasture growth patterns, with higher winter and early spring growth rates, but earlier onset of a hotter a drier summer (Figure 1). Adaptation options included a change in management to focus on increasing winter pasture growth to compensate for the loss of late spring growth, plus the selection or breeding for deeper rooted and more heat tolerant pastures in southern regions.

The soil organic carbon (SOC) case study (Figure 3) showed slower SOC accumulation under dry projections (deemed most likely), due to reduced pasture growth and associated decreased average stocking rates, which approached zero by 2090 on the low-rainfall site. The results demonstrated the extent of the uncertainty associated with soil carbon trading for farmers and the need for adaptation options that allow farms to remain sustainable and productive as the climate changes. This modelling has changed government and industry policy, from one of expecting large sequestration benefits from SOC, to a position of aiming to maintain current SOC stocks.

The wheat case study projected yield declines of between 26% and 38%, under a 'most-likely' case for RCP 4.5 by 2090, and between 41% and 49%, under a 'most-likely' case for RCP 8.5 (Figure 4). Variability also changed from the baseline under all projected RCFs and across all regions, with a standard deviation of up to 2.5 t/ha under the 'most likely' case at a site in south-eastern Australia. The study showed that southern drier wheat regions of Australia would be more impacted, requiring more transformational adaptation options. Adaptations in the less impacted regions (e.g. mixed rainfall) may include choice of cultivar and sowing times, whereas the more impacted regions may require a shift to mixed farming systems to spread risk, or even a move away from wheat cropping to other forms of agriculture.

Conclusions

Given the uncertainties inherent in the climate change scenarios and GCM predictions, there is the risk of further compounding uncertainty in downscaling to a specific location. However, for the purposes of identifying likely impacts and informing adaptation, the specific downscaling method used appears less important than understanding general trends in rainfall and temperature within a season and region. Improvements to these downscaling methods to develop future climate scenarios should rather focus on including trends in rainfall and temperature variability as well as extreme climate events, as these appear to have a greater impact on agricultural adaptation.

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SEASONAL PREDICTION FRAMEWORK FOR ATTRIBUTION OF EXTREME EVENTS IN A CHANGING CLIMATE

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At the Australian Bureau of Meteorology we have developed a system for the attribution of extreme events using our seasonal forecast coupled model, POAMA (Wang et al. 2016). The initial-value nature of the framework allows little time for the growth of model-driven biases, while allowing the full coupled response of the ocean– atmosphere–land system. We can thus analyse the specific event in question, rather than a 'class' of such events. The system provides the potential for analysis of the forecast events before they have occurred.

We have used the system to determine the influence that the last 55 years increase in atmospheric CO_2 had on two heat events (Hope et al. 2015, (see Figure 1 below); Hope et al. 2016), a very wet month (Hope et al. 2018) and an extensive frost period (Grose et al. 2018). Results align with those using other methods; for the heat there was an excess temperature anomaly of 1 ºC due to increased CO_2, the same magnitude as the temperature trend over the same period. Circulation changes driven by CO_2 increases would encourage frost development in south-west Australia, but thermodynamic changes work against this trend. Our method suggests that increasing atmospheric CO_2 did not enhance the big wet in south-east Australia in September 2016, however, some questions still remain. We have recently used the method to attempt to attribute the extreme fire weather (FFDI) in February 2017 to CO_2 increase, but there is still further development required to allow the attribution of such complex weather phenomena as fire weather.

We can also use the method to assess whether the over-riding signal that led to an extreme event was derived from the ocean, atmosphere or land surface (Arblaster et al. 2014; Hope et al. 2015).

These methods allow better contextualisation of forecast extremes, potentially providing key information to forecasters commentating on the event, or in the post-event analysis.

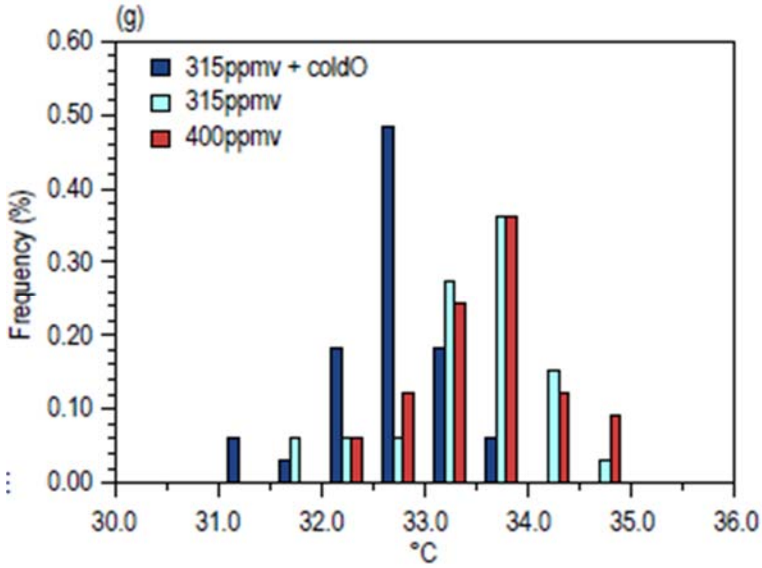

Figure 1. The ensemble spread of the forecasts under the current climate (red), the current climate with CO_2 set to 315 ppm (light blue), and a 'low-CO2' climate, with a modified ocean initial state as well as CO_2 set to 315 ppm (dark blue). (From Hope et al. 2015).

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AN OPERATIONAL LONG-RANGE CYCLONE FORECASTING SYSTEM FOR THE BUREAU OF METEOROLOGY

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Earlier work by Camp et. al (2018) on the preliminary ACCESS-S1 hindcast showed the model had multi-week skill in forecasting cyclone formation in the Southern Hemisphere. This was attributed to the model correctly simulating large scale changes in the atmosphere with the phase of the MJO. Continuing this work on the full hindcast showed monthly variation in forecast cyclone biases during the cyclone season. Results for the 2017-18 season are presented showing the effect of monthly bias correction and lagged ensembles. These are compared against 10-day forecasts generated by ACCESS-GE over the same period. A proposed operational system combining both ACCESS-S1 and GE is presented which will run in real-time during the 2018-19 season.

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ENSEMBLE METHODS FOR NEXTGEN PROJECTIONS

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Stakeholders across the Australian community want national climate projections to inform strategic decisions to reliably manage future risk. To be useful, projections information must:

- Be scientifically credible, based on the weight of evidence and available models.
- Frame and report on useful dimensions to understand the future climate – internal variability, a plausible range of emissions scenarios, a credible range of change for each emissions scenario and an assessment of confidence in projections.
- Present a credible range of change or a set of plausible scenarios – not overconfident and narrow so as to raise the real risk of maladaptive decisions, but not excessively broad where there is little value for decision-making.
- Relevant and easy-to-use in the full range of applied analyses in various arenas, including adaptation and mitigation questions.
- Be from an authoritative and trusted source to ensure legitimacy and effectiveness.

The primary source of information for previous Australian national projections has been the Coupled Model Inter-comparison Project (CMIP) ensemble of global climate models run for multiple future emissions scenarios. This has meant that traditional methods of generating ensembles could be tested and employed. Previous national projections supplemented the GCM projections with insights from available downscaling studies. State-based projects have primarily used *ad hoc* ensembles using a single method of dynamical downscaling to produce high-resolution projections that represent regional detail and processes. However, the landscape of both the uses for projections and the available data sources is changing. In response, the Earth Systems and Climate Change hub held the NextGen Projections workshop as part of developing a thoughtful strategy to ensure future success.

Different applications of climate projections, including new and emerging uses, all need different types of information, guidance and datasets to suit their needs. Emerging applications include the finance sector, who require information relevant to financial risk and exposure, and national climate projections that are consistent with international scenarios. Also, the Paris agreement targets are now firmly in the public consciousness as a target for limiting climate change, so reporting on change at these targets is highly policy-relevant. There is also a question of whether to report on scenarios that include different types of negative emissions or geoengineering.

A variety of evolving and new data sources can be used and combined in novel ways to meet these changing needs, and to ensure that the most comprehensive and scientifically robust projections are available. The new CMIP6 ensemble run for future scenarios will of course be a crucial data source for the next generation of projections, but there will be more need than ever to consider and synthesise inputs from other sources. This presents challenges to ensemble generation – in model evaluation, assessing model independence and representativeness, then ultimately model rejection and/or weighting. Data sources include:

- Non-scenario CMIP6 simulations (e.g. HighresMIP, VIACS-AB, GEOMIP)
- CORDEX2 coordinated downscaling, and also existing *ad hoc* downscaling
- Large atmosphere-only ensembles, possibly including Weather@Home and BARRA reanalysis run in projections mode
- Simulations specifically for Paris targets – HAPPIMIP, and BRACE
- Comparison of different approaches to impact assessment (e.g. ISIMIP)

ENSEMBLE METHODS IN NORTHERN AUSTRALIAN MONSOON PROJECTIONS

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Future simulations of Australian summer monsoon rainfall from climate models of the Coupled Model Intercomparison Project Phase 5 (CMIP5) show a multi-model mean projection of little change, but with large uncertainty. Under the high emission Representative Concentration Pathway (RCP8.5) scenario, the model spread includes large increases and decreases. Exploring the range of monsoon rainfall projections within the CMIP5 ensemble provides insights into the causes of model disagreement. Previous work has found that those models simulating reduced monsoon rainfall tend to have larger biases in sea surface temperatures in the western equatorial Pacific, and are therefore less credible (Brown et al. 2016). In addition, the monsoon rainfall response is strongly correlated with the spatial pattern of sea surface temperature warming.

In the lower emission RCP4.5 and RCP2.6 scenarios, the influence of non-greenhouse gas forcing, including anthropogenic aerosols, becomes more important. The prescribed decline in aerosols over the 21st century produces a rainfall response that is of similar magnitude to increases due to greenhouse gases, with changes in the interhemispheric temperature gradient driving a northward displacement of tropical rainfall. Those models which include a representation of aerosol indirect effects therefore project drying under medium and low emissions scenarios, whereas models without the aerosol indirect effect project a wetter Australian monsoon.

Difference in climate model projections for Australian monsoon rainfall can therefore be explained by a combination of factors including model mean state biases, differences in the spatial pattern of warming, differences in climate sensitivity and the representation of aerosol-cloud interactions. This information will contribute to more robust projections with improved measures of uncertainty. The use of an ensemble of climate models is necessary to facilitate this approach, as a single model, even one with the most comprehensive model physics or highest resolution, cannot provide insight into the sensitivity of projections to particular processes or forcings.

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THE WEATHER@HOME REGIONAL CLIMATE MODELLING PROJECT FOR AUSTRALIA AND NEW ZEALAND

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Overview

A climate modelling project has been developed for regional climate simulation and the attribution of weather and climate extremes over Australia and New Zealand. The project, known as weather@home Australia–New Zealand (Black et al. 2016), uses public volunteers' home computers to run a moderate-resolution global atmospheric model with a nested regional model over the Australasian region. By harnessing the aggregated computing power of home computers, weather@home is able to generate an unprecedented number of simulations of possible weather under various climate scenarios. This combination of large ensemble sizes with high spatial resolution allows extreme events to be examined with well-constrained estimates of sampling uncertainty. This presentation provides an overview of the weather@home Australia–New Zealand project, including initial evaluation of the regional model performance. The model is seen to be capable of resolving many climate features that are important for the Australian and New Zealand regions, including the influence of El Niño–Southern Oscillation on driving natural climate variability. To date, model simulations of the historical climate have been successfully integrated over the period 1985–2014 in a time-slice manner. In addition, multi-thousand member ensembles have also been generated for the years 2013, 2014 and 2015 under climate scenarios with and without the effect of human influences. All data generated by the project are freely available to the broader research community.

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MODEL DEPENDENCE IN CLIMATE ENSEMBLES

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Modelling groups internationally share literature, parameterisations, data sets and even sections of model code, so the potential for shared biases among climate model simulations from different institutions is clear. Yet when examining projection estimates, we have no other option than to use a range of different climate models as a proxy for multiple working hypotheses, hoping to obtain independent estimates from different models.

The community has no agreed metrics for quantifying model dependence, which potentially affects both the mean and spread of ensemble-based climate change estimates. Explicit attempts to address dependence within climate model ensembles are rare. While a handful of techniques to address this issue have been published, they are typically statistically involved and seem to adopt incommensurable definitions of model dependence. Internal variability and limited observational data clearly make this problem even more difficult.

The lack of observational constraint for the evaluation of individual process representations, and the epistemological holism that results from it, makes defining dependence in terms of shared model structure difficult. Where process representations are tightly constrained by physical laws or observational data, models would ideally agree. It is only for poorly constrained processes, or those where computational limitations mean they can only be approximated, that we want different models to offer a variety of independent approaches. This distinction highlights the interconnectedness of model independence and model performance in any workable approach that quantitatively accounts for model dependence.

This talk will give a very brief introduction to existing approaches that deal with model dependence, before trying to contextualise them in an overarching framework.

CLIMATE HAZARDS AND EXTREME WEATHER PROJECTIONS FOR AUSTRALIA

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Introduction

Natural disasters in Australia are commonly associated with weather and ocean hazards. These hazards, and costs associated with their impacts, are likely to change in a warmer world. Consequently, there is an evolving need to better understand and communicate the influence of climate change on extreme weather and ocean hazards. This would have large benefits, through being able to manage a more tightly constrained uncertainty range, for sectors such as energy, finance, biodiversity and emergency management.

This paper describes various approaches that can be used to examine the influence of climate change on extreme weather and ocean conditions, including ensemble approaches and new downscaling projections for Australia. A synthesis of available knowledge is then provided on a range of climate hazards for Australian conditions. While noting that regional variations can occur, these knowledge products are intended for general use around communicating the influence of climate change on a range of extreme weather and ocean hazards in Australia.

Ensemble approaches and development of new downscaling projections

Ensemble approaches can help understand uncertainties, including multi-model ensembles or multi-method approaches (e.g., ensembles of ensembles). Given the substantial uncertainties around projected future changes in some extreme phenomena, approaches that synthesise all available lines of evidence can be useful, including based on combining modelling, observations and physical process understanding. However, even with that type of synthesis approach it can still sometimes be difficult to know how much of the plausible uncertainty space has been sampled, in which case there is a need to effectively communicate this uncertainty as accurately as possible (as is done in the following section ‘General summaries on future changes in hazards’).

There is a relatively small number of downscaling methods with projections of future climate available for Australia, as compared to other regions of the world such as Europe and North America where larger ensembles exist based on multiple regional modelling methods. To help address this need for the Australian region, recent work has tested dynamical downscaling from global climate models (GCMs) using a similar framework to that used recently for the BARRA reanalysis produced by the Bureau. This projections modelling framework was named similar to BARRA, but with a P standing for projections rather than a R for reanalysis: **B**ureau of Meteorology **A**tmospheric High-**R**esolution **P**rojections for **A**ustralia (BARPA).

The idea behind BARPA was to produce dynamically downscaled projections of future climate that were as seamless as possible with the BARRA reanalysis, including to help improve our understanding of extreme weather projections as needed for climate risk applications (e.g., national vulnerability assessments and disaster risk reduction). The CCSM4 model (from the CMIP5 ensemble of GCMs) was selected for the initial runs for developing this downscaling method. Historical time slices were selected to allow an examination of the ability of the downscaling to improve the representation of features such as convection in the tropics (including thunderstorms over the Tiwi Islands) as well as low pressure systems in the extratropical regions of Australia. It is intended that there will be further development of BARPA, including eventually based on multiple GCMs and different future emissions scenarios, leading to a useful set of projections that could help contribute to the broader efforts around multi-method ensembles (such as forming part of the CORDEX set of downscaling and the next generation of projections for Australia).

Improvements in multi-method approached (ensemble of ensembles based on multiple regional models) for Australia could help better-constrain uncertainties around some extremes for which the influence of climate change is largely unknown at the moment (e.g., for the risk of extreme wind events associated with severe thunderstorms). Further details on the influence of climate change on weather and ocean hazards, including uncertainties, are provided in the next section.

General summaries on future changes in hazards

This section presents a synthesis of available knowledge around the influence of climate change on different types of natural hazards that impact Australia. Table 1 presents a concise overview of this. General talking points are provided after the table for each individual hazards type. These talking points are intended for general guidance, for practical applications around communicating climate risks, while also noting some regional variations.

Table 1: Summaries on the influence of climate change on weather and ocean hazards.

Hazards type	General influence of climate change
Extreme heat events	More frequent and intense extreme heat events
Bushfires	More dangerous bushfire conditions in some regions, particularly in southern and eastern Australia, including an earlier start to the fire season
Extreme rainfall	More intense extreme rain events are likely throughout Australia, with potentially large increases for short duration events
Flooding	Increased risk of flash flood in urban areas, and larger uncertainties for other types of flooding

Sea level rise and storm surge	Sea levels will continue to rise around Australia, increasing storm surge risk
Thunderstorms	Potentially large increases for short-duration rainfall extremes, with larger uncertainties for extreme winds, tornadoes, hail and lightning
Cyclones and low-pressure systems:	Fewer but potentially more intense cyclones in some regions, including tropical cyclones and Australian East Coast Lows

Climate change background

Based on the scientific evidence now available, it is clear that human-caused climate change has already influenced various weather and ocean hazards in Australasia.

Scientific literature has well-established human-caused greenhouse gas emissions are the primary cause of climate change observed during the 20th century and continuing into the 21st century. Indicators are long-term trends such as global warming and rising sea levels.

Increasing atmospheric greenhouse gas concentrations into the future will continue amplifying many weather and ocean hazards.

Extreme heat events

Average temperatures across Australasia have increased by about 1°C since 1900 due to human-caused greenhouse gas emissions.

The warming trend has led to an increase in the number of extreme heat events that have occurred.

Multi-day heat wave events have increased in frequency and duration across many regions of Australia; it is almost certain climate change will continue to worsen the impacts of extreme heat events, with longer heat waves, more frequent extreme heat days, and temperatures above historical records.

Bushfires

Human-caused climate change has already influenced the frequency and severity of dangerous bushfire conditions in Australasia and other regions of the world.

Significant changes have been observed in recent decades towards more dangerous bushfire weather conditions in some regions of Australasia, indicating a longer and more severe fire season particularly in southern and eastern Australia.

Bushfire weather conditions in future years are projected to increase in severity for many regions of Australasia.

In Australia, there is high confidence that bushfire weather conditions in the future will increase in severity in southern and eastern regions.

Extreme rainfall

There is evidence climate change has increased the intensity of extreme rainfall events in some regions.

Global warming can have a direct influence on extreme rainfall potential, as the moisture capacity of the atmosphere increases with temperature by about 7% per degree of warming.

Short-duration extreme rainfall events as produced by thunderstorms or tropical cyclones could potentially increase in intensity by about 15% per degree of warming in some cases, while noting a range of plausible values above and below this best estimate.

Flooding

An increase in flash flooding risk is possible due to the potential of increased intensity of short-duration rainfall events, particularly for urban environments where soil moisture has less influence on flood risk.

When combined with increasing sea level, projected increases in extreme rainfall intensity suggest flooding will likely increase in frequency and magnitude in the future for many coastal and estuarine regions throughout Australasia.

Sea level rise and storm surge

Global warming is causing sea levels to rise due to the combined effects of melting glaciers and thermal expansion of the oceans, with a global average rise of about 20 cm since the mid-19th century, with similar trends in Australasia.

Sea level rise has accelerated in recent decades, with a global increase of 2.6-2.9 mm/year from 1993 to mid-2014.

These projections do not fully capture the potential contribution to sea level rise from the large ice sheets (Greenland and Antarctica), whose response to global warming is uncertain and possibly underestimated, with rises exceeding 2.4 m being physically possible later this century.

Due to rising sea levels, the frequency and magnitude of coastal flooding is expected to increase significantly this century, regardless of potential changes in storm events.

Thunderstorms (including hail, lightning and tornadoes)

Trends in extreme wind events, including as caused by thunderstorms, are difficult to determine in Australia due to a lack of a long-term high-quality observations.

Future changes in thunderstorm hazards are relatively uncertain for lightning, hail, tornados and extreme wind gusts, with potentially large increases for short-duration rainfall extremes.

Cyclones and low-pressure systems

Climate change is likely to affect cyclone activity in a number of ways, with these changes being variable between different types of cyclones.

Observations show a downward trend in the number of tropical cyclones that have occurred in recent decades in Australasia.

Fewer east coast lows are likely to occur in the future near Australia, while noting that those that do occur could potentially cause more severe coastal hazards including due to rising sea levels as well as heavier rainfall.

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ENSEMBLE SELECTION FOR HYDROLOGICAL PROJECTIONS – PRELIMINARY STEPS

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The Bureau of Meteorology has undertaken to develop a national Hydrological Projections service, and we are in the development stage. A first step in this process is to determine the best way to develop an appropriate ensemble of projections.

There are a number of steps and choices in developing hydrological projections (Figure 1), and these place constraints upon the ensemble that can be used, and at times, pragmatic choices must be made. Earlier efforts (ISI-MIP: Hempel et al. 2013; Victoria: Potter et al. 2018) have used an ensemble of opportunity, based upon the climate model simulations and downscaled data that was available, that also had output of the variables required to run their hydrological models.

In this presentation, we will outline the steps and choices made in the first stages of choosing the ensemble of climate model projections to be used in the Bureau of Meteorology's hydrological projections project.

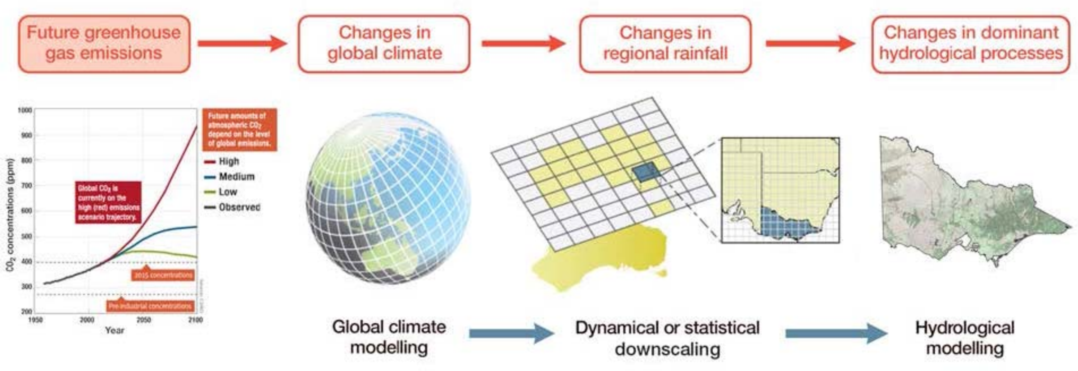

Figure 1. From (Hope et al. 2017). Four steps in developing hydrological projections. These four steps are also the points at which choices can be made, and so create an appropriate ensemble to capture the range of uncertainty. Choices can be made about the scenario(s), the GCMs, the downscaling method and the hydrological model.

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EXPERIENCE FROM USING ENSEMBLE METHODS IN CLIMATE AND WATER SERVICES

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Introduction

Currently there is a fast growing development of climate services across the world addressing various geographical domains, scales and societal sectors. The need of readily available high-quality climate data became urgent with the Paris Agreement in 2015, which in addition to mitigation also highlight the necessities of adaptation measures (United Nations, 2015). The numerous existing services differ a lot in design, data content, accessibility, formats, user friendliness and it is often unclear who the target user is. Accordingly, the definition of a climate service varies a lot (c.f. EC, 2015; US NRC, 2001; WMO, 2015). In general, there are two main categories of services provided; (1) the general and web-based, and (2) the tailor made in dialogue with a specific user. The two categories could well be interlinked, when so called 'Knowledge Purveyors' use the first service to provide the latter (e.g. Donnelly et al., 2018).

This presentation sums-up recent experiences from working with various climate services; (i) in Sweden by the national weather and water service, (ii) in Europe and globally from proof-of-concepts for the Copernicus Climate Change Services (C3S) operated by ECMWF on behalf of the European Union, and (iii) in several R&D projects, aiming to advance climate services by national and European research councils. It will start with a short Demo of the components suggested to be part of web-based climate services, followed by the importance of ensemble methods in the data production chain, and finally, some lessons learnt from user uptake.

Suggested components of a web-based climate service

The climate services discussed here should provide climate data to a user, who needs data and information when working with climate adaptation. The service is the interface between climate science and society, trying to communicate future impacts from climate change. Climate science and tools are often demanding, both in skills and time. In society, there are many potential users of climate data and they have very different needs and capacity. To be useful, the service thus needs to communicate differently to different user groups and convert data into information that can be received by specific user groups. A large part of the service should therefore be dedicated to user guidance, training and showcases, but this is where many climate services fail at present.

Different user communities (e.g policy makers, authorities, managers, consultant engineers or scientists) will use the data in completely different types of applications and therefore need to access it in different forms (Fig. 1). They will face completely different problems in their applications and therefore they also need different user support and means of communication from the data provider (i.e. the scientific community). There is no "one-size-fits-all" for climate services but they must be tailored in each component to reach out to specific user communities. This is probably where there is most potential at present for increasing user-uptake from climate services and accelerating climate adaptation.

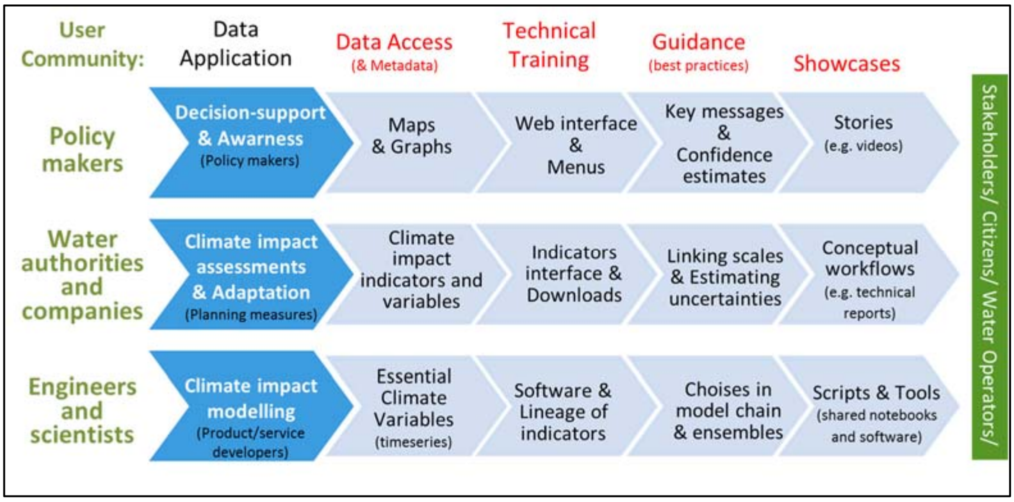

Figure 1. Components (red) in a climate service when tailored (light blue) for different user categories (green) and applications (dark blue).

Ensemble methods in the data-production chain of climate impacts

The climate impact indicators provided in a climate service are often the end result of a long chain of model simulations and statistical calculations (Fig 2.). Each step in the production chain includes large uncertainties and therefore an ensemble of projections is normally presented. The ensembles contain a spread of values that reflect the lack of knowledge, for instance about initial conditions, sensitivity of processes, future emissions and natural variability (e.g. Kjellström et al., 2013). Most uncertainty in near-time projections refers to natural variability, which still remains difficult to describe due to low spatial resolution in observation networks and thus unknown initial conditions. On a longer time scale, most uncertainty refers to future concentrations of greenhouse gases in the atmosphere (RCP's), which depend on societal evolution and implementation of mitigation measures. Additionally, uncertainties refer to future circulation patterns involving atmosphere and ocean dynamics; as the atmospheric system is quite chaotic, it is possible to only make predictions for the nearest days based on known initial conditions - the climate time-scale is not yet possible to predict. Instead, climate modellers explore sensitivities and make assessments about future climate change by using different scenarios for the future, producing projections of climate change in a range of different climate models starting from different initial conditions. The result is an ensemble of climate projections, but ensemble methods are also needed for the production steps that follow in impact assessments, as they may be just as uncertain.

Bias adjustments are normally performed before impact analysis, to make the climate-model results correspond to observations during a reference period. However, the observations at specific points may not be representative, and methods are very sensitive to gauge density (e.g.

Olsson et al., 2016). Moreover, various methods may lead to different implications for the final analysis, e.g. inconsistency between corrected variables if this is done separately. The final part of the model chain, the hydrological impact models, may respond differently to climate change due to different interpretation of drivers for flow generation, from model parameter values or assumptions in the model structure (e.g. Krysanova et al., 2018).

Water management is always local, and the local scale is already exposed to large variation in weather patterns. This means that climate impact may not be evident on a year to year basis, but some events may become more frequent, or prolonged, if analysed over a longer time period. Therefore, climate impact assessments often use 30 year averages to explore changes. In practice this may be too short a period for local conditions as they are so variable. If the trend is small and the variability large (often in precipitation and river flow) it may be very difficult to detect changes beyond natural variability.

Most climate services try to give examples on how climate change may be manifested in the future, given some major sources of uncertainty. However, for specific applications, some models and some impact indicators may be more trustworthy than others (e.g. Donnelly et al., 2018). Here the users need guidance for climate adaptation. Traditionally, it has been argued that it is impossible to judge which models perform better under future climate change, and thus, it is the best to a use range of models (an ensemble). Research has shown that an ensemble of models gives a more accurate prediction of future climate impacts than even the best individual model (e.g. Krishnamurti et al., 2000; Tebaldi and Knutti, 2007). For practical reasons, statistical methods on how to choose a sample from the ensemble but still keep the ensemble spread has been suggested (e.g. Pechlivanidis et al., 2018). However, recently, it has also been argued that more qualitative methods should be used, as some members in the model ensemble may be less trustworthy (Krysanova et al., 2018; Donnelly et al., 2018).

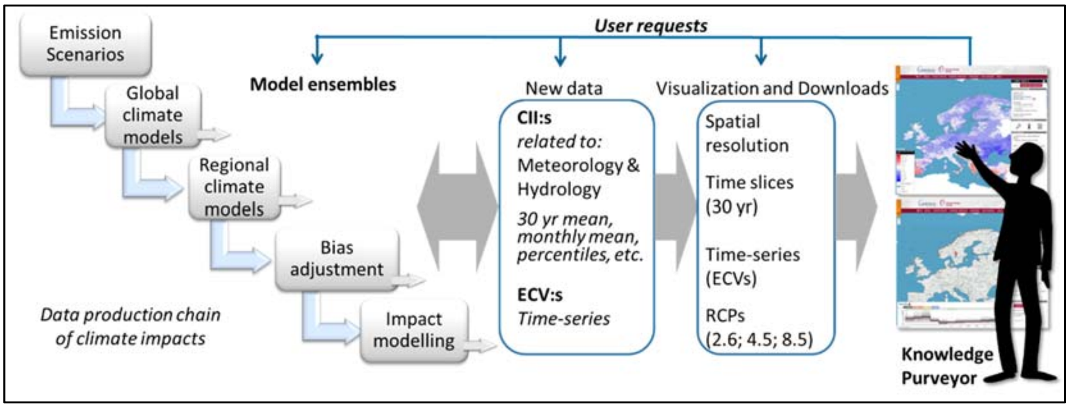

Figure 2. Ensemble methods are included in each step of the production chain of climate impacts to be visualized and downloaded based on user (e.g. a knowledge purveyor) choice in the climate service.

Lessons learnt from user uptake

The experiences from working with users of climate and water services, and co-development of services involving different stakeholders across Europe, have resulted in some main lessons learnt:

- Climate science is difficult with large uncertainties (requesting ensemble approaches) and data tailoring for climate adaptation is time-consuming, therefore the concept of 'Knowledge purveyors", i.e. consultant engineers, is essential for user uptake of climate services. This intermediate expert group should be in focus when developing climate services for water impact adaptation.

- Know-how in tailoring data is essential for a wide uptake of climate services. The large-scale data need to be further adjusted to observations and merged with local data sources. For this, the Knowledge purveyors need to be educated and web-based services should thus be equipped with online methods, like webinars, video conferences, social-media groups, a Forum, user support and offer various face-to-face meetings, like workshops at dedicated hands-on training.

- Quick and easy access to climate-impact data for download without having to run a full production chain (involving climate and impact modelling) probably is the single most important element of a climate and water service. Climate indicators were in general appreciated as very useful. However, the service need to address specific user communities regarding format, key-messages, meta-data and fact sheets that address their needs and level of competence. Moreover, the users need to be ensured about service sustainability, data consistency, and robustness of results.

Acknowledgements

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USING THE EUROCORDEX ENSEMBLE TO EXAMINE THE IMPACTS OF 1.5, 2 AND 3 °C GLOBAL WARMING ON EUROPEAN HYDROLOGY

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Introduction

Global warming is expected to cause large-scale changes to the terrestrial water cycle affecting water availability for cities, energy production and agriculture, river navigability, flood risks and more. While impacts of climate change on the water cycle in Europe are well studied (e.g. Jiménez Cisneros et al. 2014), it is less well known what the impacts associated with various levels of global warming will be. Prior to the 21st session of the Conference of the Parties (COP21), a goal of +2°C warming globally above preindustrial levels was internationally accepted as the level required to prevent dangerous anthropogenic interference with the system (UNFCCC 2010). Since the 2015 COP21 Paris agreement, a more ambitious mitigation objective to "Hold the increase in the global mean temperature (GMT) to well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C" has been proposed (UNFCCC 2015). At the same time, if the current trajectory of greenhouse emissions continues, we could end up with more than 3 °C GMT rise (Sanford et al. 2014). Hence 1.5, 2 and 3 °C GMT rise are important milestones, not only for mitigation but also to understand the expected impacts of climate change.

This study (Donnelly et al. 2017) outlines a novel methodology to quantify the impact of these warming levels on the terrestrial water cycle in Europe. It uses the EUROCORDEX ensemble of regionally downscaled climate projections and an ensemble of five continental and global-scale hydrological models. An uncertainty in the methodology is tested by repeating the analysis for 2°C of warming using different ensembles, driven by different representative concentration pathways (RCPs). Finally, the impacts of climate change at 1.5, 2 and 3°C global mean temperature rise above pre-industrial levels are presented for a number of indicators of water-related change across Europe.

Data and Methods

This study makes use of the latest ensemble of high-resolution climate model outputs from the "Coordinated Regional Climate Downscaling Experiment" (CORDEX, Jacob et al. 2014). The project uses an ensemble of general circulation models (GCMs) from the climate model intercomparison project, phase 5 (CMIP5, Taylor et al. 2012) to force regional climate models (RCMs). A subset of 11 projections was chosen to represent the spread of the full CORDEX ensemble using cluster analysis (Moss et al. 2010). They are based on five unique GCM/RCM combinations (four GCMs and four RCMs) and three concentration pathways, representing a low-, medium- and high-emission scenario (RCP2.6, 4.5 and 8.5), combined in different ensembles for the three warming levels (1.5°C, 2°C and 3°C GMT rise).

The method to define warming thresholds in climate models follows that of Vautard et al. (2014). Scenarios that pass the target warming level are used as snapshots in time representing these levels of warming. This is necessary because the number of climate models stabilising at each of these warming thresholds are not sufficient. The impacts of climate change at 1.5, 2 and 3°C GMT rise are assessed by quantifying the change in hydrological indicators for the 30-year period centred at the year when each GCM reaches the defined increase in GMT relative to preindustrial levels (1881–1910). These temperature thresholds are reached at different times by each GCM. For example, the climate in a 1.5 °C warmed world is calculated using MPI-ESM-LR/CSCRemo/RCP2.6 for the period 2035-2064, in ensemble with EC-EARTH/SMHI-RCA4/RCP2.6 for the period 2028-2057, EC-EARTH/KNMI-RACMO22E/RCP4.5 for the period 2018-2047 and four other ensemble members.

The RCP8.5 runs reach the +1.5°C threshold very early in the twenty-first century when the uncertainty from the initial state of the climate models is still very high, so the ensemble for +1.5°C is made up of the lower emission RCPs: RCP2.6 and RCP4.5. For +3°C, only some of the RCP8.5 simulations reach +3°C by the end of the century. Therefore, the ensemble for the +3°C warming only consists of RCP8.5 (high-emission) runs. To study the sensitivity of the impacts to the choice of concentration pathway, the impacts at 2 °C were calculated twice: (a) for an ensemble of the low-emission pathways (RCP2.6 and 4.5) and (b) for an ensemble of the high-emission pathway (RCP8.5). For details of the methodology, see Donnelly et al. (2017).

The dynamically downscaled projections were each bias-corrected to the E-OBS gridded, interpolated observations data set for Europe. The bias-corrected data was subsequently used to force five hydrological models over Europe (Donnelly et al. 2017). They include model concepts varying from land-surface schemes (VIC, Liang et al. 1994), to process-based hydrological models of varying levels of complexity (LISFLOOD, Burek et al. 2013; WBM, Vörösmarty et al. 2000; and E-HYPE, Donnelly et al. 2016) and a coupled water and carbon cycle model with vegetation dynamics (LPJmL, Schaphoff et al. 2013).

Finally, the changes to a few simple indicators, indicative of the climatic development of aspects of the water cycle relevant for users, were quantified at each warming level. These changes in water-cycle indicators may then be used to infer potential impacts on water-related sectors. The following hydrological indicators were calculated for all of Europe:

1. Evapotranspiration: Mean annual evapotranspiration (indicative of water demand/use)
2. Runoff: Mean annual runoff (indicative of available water resources, e.g. for agriculture, water supply, navigation, etc.)
3. High runoff: Mean annual maximum runoff (indicative of recurring high flows and flooding)
4. Low runoff: Mean annual low runoff (mean of annual 10th percentile runoff, indicative of dry conditions/drought)
5. Snowpack: Mean annual snow water equivalent (SWE) maximum (indicative of snow storage for hydropower production and tourism)

Note that while the warming levels of 1.5, 2 and 3°C are defined relative to preindustrial levels, the impacts of the change are analysed relative to a more recent historical period, 1971-2000.

Results

Summarised across Europe, there are quantifiable differences between the impacts at different warming levels for most variables (Fig. 1). This is indicated by the slope of the fitted line of the scatter plots (far left and far right columns). For precipitation and evapotranspiration, the changes are greater at each subsequent warming level, e.g. where precipitation is projected to decrease with increased warming, these decreases become larger. Similarly, projected increases in precipitation become higher. For mean annual runoff, changes at 2°C are greater than at 1.5°C, but differences are less discernible between 2 and 3°C (with the exception of projected large decreases in runoff).

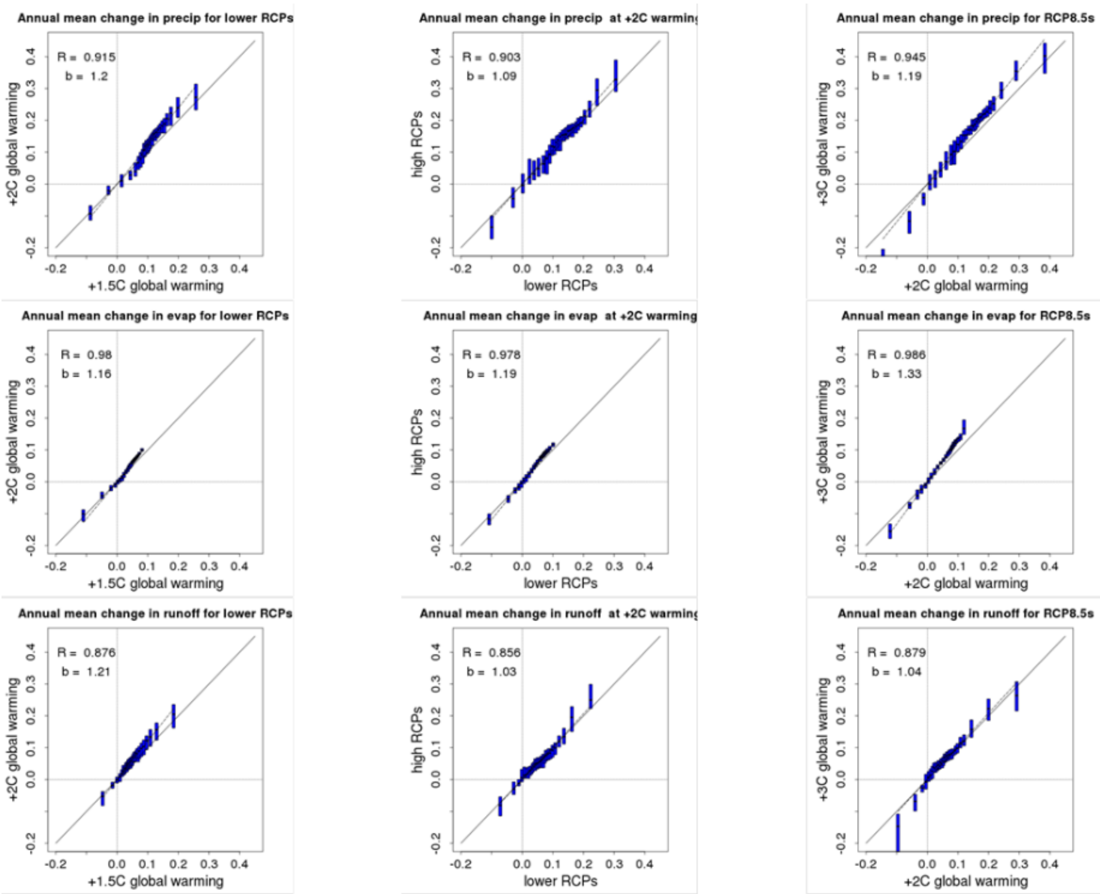

Fig 1. Comparison of ensemble mean changes in hydrological indicators at different levels of global warming (left and right columns) and for different RCPs (middle column) for +2 °C. Changes are relative to the baseline period. (Donnelly et al. 2017).

Some of the uncertainty related to the appropriateness of building the climate model ensembles on different RCPs is assessed by comparing the ensembles using the high and low emission RCPs for the 2°C warming level (Fig 1, central column). Here we see that although there are differences in results between the two methodologies (i.e. deviation from the 1:1 line, central column), these differences are generally smaller than those between the warming levels (left and right columns). For example, changes to precipitation increase more between warming levels than between the ensembles used to define the 2 °C warming level. Exceptions are evapotranspiration, snowpack and for all indicators, those grid cells with the largest changes (see Donnelly et al. 2017). We also compared the sensitivity of the different to warming. For 2 vs 1.5°C, there is less spread in HM response than the magnitude of the projected changes, but for 3 vs 2°C the spread is larger than the ensemble mean changes indicating HM uncertainty in these results. For the 2°C comparison, all models produce similar changes.

Spatially, most of central, western and northern Europe shows robust increases in total annual precipitation for all levels of warming. Changes in precipitation are negligible or uncertain in central western and southern Europe and UK, even at the 3°C warming level (Fig. 3). The decrease in precipitation projected around the Iberian coast becomes larger and more widespread with increasing warming. Changes to runoff generally follow the spatial extent of changes in precipitation but are of a smaller magnitude and less robust. Robust increases in runoff are seen for parts of Scandinavia, northeast Europe, Austria, the northwest Balkans and Hungary and the extent of the robust regions expands from 2 to 3°C. For all levels of warming these runoff changes are strongest in winter.

Discussion and Conclusions

At the regional and continental scale, our results support the hypothesis that a higher level of global warming will lead to more severe impacts on precipitation, evapotranspiration, runoff and snow for most of Europe. Impacts increase in severity and spatial extent as warming increases. In particular, our results show a considerable difference between the impacts on mean runoff and low runoff (Donnelly et al. 2017) at 1.5 and 2°C warming indicating the impact that even a small increase in global warming has on European water resources.

One limitation in this study is the transient nature of the climates that are assessed from the climate model simulations at different warming levels for only short (30-year) time periods. The advantage of this approach is that analysing an ensemble of projections for different time periods with a common global temperature change removes some of the uncertainty resulting from the GCM's climate sensitivity (Vautard et al. 2014). However, the method relies on the assumption that for a given warming, the impacts of climate change are the same, regardless of the time taken to reach it or whether equilibrium has been reached. One argument against this is that systems, such as the ocean, might take longer to adjust to the 2 °C period as might changes in biogeochemical processes including changes to evapotranspiration and growth of vegetation at different CO_2 concentrations in the atmosphere. To some extent, this is investigated by quantifying the 2°C changes using two ensembles forced with different RCPs which reach the warming level threshold at different times (mean midpoint of 2040 vs 2061). The results showed that for the different 2°C ensembles tested, the impacts at the same warming level increased with increasing RCP; however, these differences were nearly always smaller than the differences between the different warming levels, supporting the hypothesis that increased warming leads to increased hydrological impacts.

Regarding HM uncertainty, despite the large variations in HM structure, the spread in HM response for runoff was smaller than the projected changes at lower warming levels; however, for higher warming levels (2 to 3°C), the spread in HM response was larger than the projected changes (Donnelly et al. 2017), indicating large uncertainties in hydrological response at higher warming. This is thought to be mainly due to the different formulations and parameterisations of potential evapotranspiration in the different models. Overall, there are large uncertainties resulting from the GCM, RCM and HM choices and representativeness of their spread, the choice of bias-correction methodology as well as the omission of vegetation CO_2 response, anthropogenic impacts on the water cycle and landuse use change in the HMs. However, the key message, that impacts on the water cycle increase from 1.5 to 2 to 3 °C warming, is robust.

In conclusion, the impacts of climate change on mean, low and high runoff and mean snowpack (not shown here, see Donnelly et al. 2017 for all results) in Europe increase with increased warming level. Changes to runoff are more intense at 2°C compared to 1.5 °C and become more widespread at 3 °C. The fact that the hydrological impacts of climate change are geographically more widespread for higher levels of warming implies that larger regions and more countries will be impacted by the effects of climate change in sectors where water plays an important role.

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CASCADING ENSEMBLE OF UNCERTAINTIES IN CLIMATE AND HYDROLOGICAL MODELLING TO PREDICT FUTURE WATER AVAILABILITY AND RIVER FLOW CHARACTERISTICS

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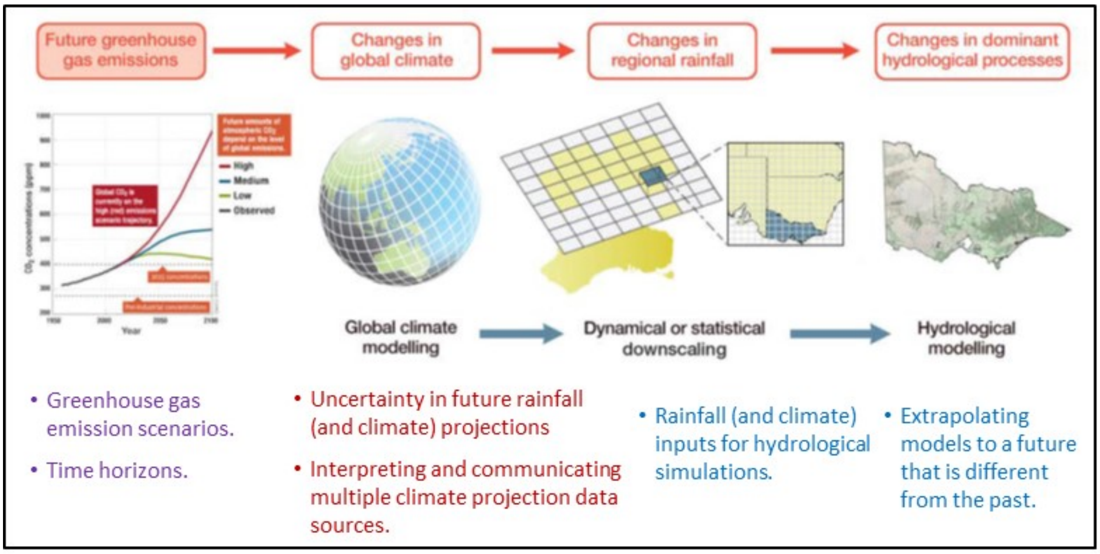
Climate change impacts on water represent a cross-cutting issue affecting people, agriculture, industries and ecosystems. Robust projections of future water availability and hydrological characteristics are needed to assess climate change impacts on water and related sectors and to design and implement adaptation options.

This presentation will discuss the limitations, and science challenges and opportunities in predicting climate change impact on future water availability and river flow characteristics.

These include:

- interpreting and communicating climate change projection data from many different sources and global climate modelling and climate downscaling products;
- robustly bias correcting downscaled rainfall and climate data for use in hydrological modelling; and
- adapting and extrapolating hydrological models to predict a future that is different from the past (higher temperature, enhanced CO_2, changed precipitation patterns).

The interconnected modelling components, and the main sources of uncertainty, are shown schematically below. Research progress in these areas will lead to more robust next generation climate and water projections to better inform risk-based planning and adaptation options.



ENSEMBLE METHODS IN DOWNSCALING PROJECTIONS

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Due to time and resource limitations, creating a regional climate (dynamically downscaled) projection ensemble requires choices to be made concerning the set of Global Climate Model (GCM) projections to downscale from, and the set of regional climate models (RCMs) to downscale with. Most commonly these choices have been made based on convenience. That is, both the global and regional models are chosen based on familiarity, and ease of access. Occasionally model performance has also been considered (Corney et al. 2010). Often the limitations are such that the RCM and GCM subsets are relatively small, leading to a biased regional projection ensemble that under-samples the uncertainty in the future climate. Attempts have been made to increase the sampled range such as the sparse matrix GCM-RCM pairing adopted in the North American Regional Climate Change Assessment Program (NARCCAP; Mearns et al. 2013). Explicit consideration of the full GCM ensemble spread has also been suggested (Whetton et al. 2012) and implemented within a regional projection project (Evans et al. 2014). This talk will discuss two questions: What are the desired properties of the regional climate projection ensemble? And how can we create our ensemble, within resource constraints, to achieve them?

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ENSEMBLE METHODS FOR DROUGHT PROJECTIONS

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Abstract

The term ‘drought’ generally refers to a period with a deficit of water relative to normal conditions. Defining the norms can be problematic since they are ‘not absolute’, particularly in the non-stationary context of climate change. Also, different systems (or applications) use water in different ways and at different periods. Thus, there are hundreds of drought indicators (or indices) available, which are commonly categorized into four types of drought: meteorological drought (below-normal rainfall), agricultural or soil moisture drought (below-normal storage in saturated zone), hydrologic drought (below-normal water availability in streams, lakes and/or groundwater) and socioeconomic drought (when water supplies cannot meet the demand). Likewise, the approach to define the onset, end and degree of severity of the drought event can vary and is usually arbitrary.

There is no single agreed definition of drought, and some form of rainfall deficit in a region relative to the long-term average is commonly used. In the context of climate change impact and vulnerability assessment, a useful definition of drought may depend on what is appropriate to the activity, time and place under consideration.

Work on projections for drought in Australia commenced in early 1990s, after which there was little activity on this topic until the late 2000s, continuing to the present. The projections of drought characteristics (e.g. duration, frequency and intensity) are usually informed by climate projection data from of Global Climate Models (GCMs). The range of possible futures should represent, at least, two broad modelling uncertainties: method used to develop climate change scenarios, and the drought indicator and/or model(s) used to estimate the future drought. There are also sub- and sub-sub-uncertainties within each of these sources of uncertainty that need to be taken into account.

Ensemble results often vary with methods and regions, according to studies. For example, the projected future drought frequency calculated from raw and bias corrected GCMs simulations data can differ widely. In some cases, projections informed by better performing GCMs can result in a decreased ensemble range and in a clearer sign of the likely change in drought intensity in some regions in Australia compared to those built on all available GCMs data. Projections also depend on the drought indicator used, drought characteristic and timescale under consideration. Other methodological challenges, including how to communicate ensemble projections, will also be highlighted in the talk along with some thoughts about the future.

USING ENSEMBLE IN DERIVING BASELINES FOR VICTORIAN WATER ASSESSMENT

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Introduction

The baseline is a period which has been chosen to best represent the current climate of a region and serves two main purposes: 1) it is used as a reference against which recent observations are compared and 2) it can be used as a benchmark to evaluate the looming changes in climate for planning and management processes. Hope et al. (2017) pointed out that baseline selection poses a significant source of uncertainty in defining the exact magnitude of the projected changes in Victoria's climate.

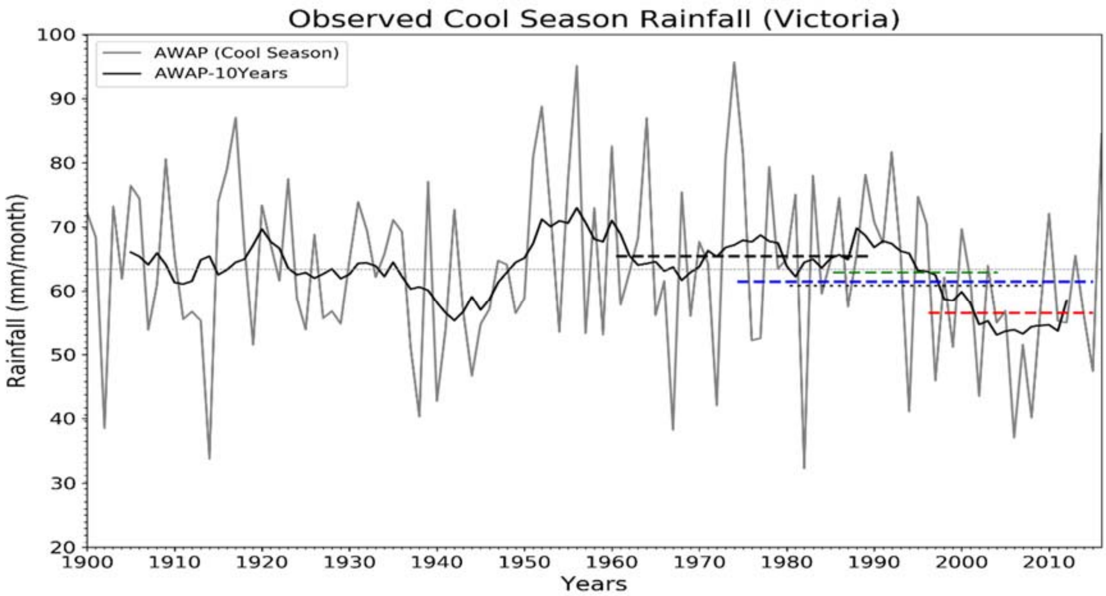
Key requirements for a baseline are that it should be of sufficient duration to encompass the range of natural climate variability, but, given that the climate is likely to be changing due to anthropogenically-driven climate change, the baseline should also be of short enough duration so as to represent the current state of the climate, and minimize the chance of any climate shifts within the baseline period. The World Meteorological Organization (WMO) recommends using a period of at least 30 years (e.g. 1981–2010) as a baseline to compute the climatological standard normals (WMO 2017), while IPCC has used the 1986–2005 period as a baseline in its fifth assessment report (IPCC 2013) as a reference period in its assessment of climate change.

For rainfall however, a number of studies have found that 30 years or less is not long enough to adequately represent the range of natural variability, especially when it is used as a predictive indicator of the conditions likely to be experienced in a given location. Victoria just experienced its driest cool season (April – October) rainfall for the last 30 years compared to any 30-year period in the historical record from 1900–2016 (Timbal et al. 2016). Research undertaken during the South Eastern Australian Climate Initiative (CSIRO 2012) and the Victorian Climate Initiative (Hope et al. 2017) have shown that the baseline climate is changing as the assumption of a stationary climate has been challenged by the recent persistently dry conditions. Victorian rainfall trends include a known influence from climate change, thus this recent period could be representative of the best baseline to use. However, the projected rainfall reductions for 2030 across the region are smaller than the observed declines over the last decades. Given this discrepancy, do the recent decades represent a true baseline, and a good estimate of the climate going forward, or are they unusually dry? Is any historical period truly representative of the current state of the climate or the expected climatic conditions over the coming decade? These concerns lead to questions about how best to characterize the baseline climate.

Given the concerns above, the current guidelines for "Assessing the Impact of Climate Change on Water Supplies in Victoria" developed by the Department of Environment Land, Water and Planning (DELWP) recommends using a longer period of 1975 to date as a current baseline period for water resources planning and management. Is this the best estimate of the current baseline for Victoria's rainfall?

Research

The Bureau of Meteorology recently began research on baselines for the Victorian water sector as part of a new program co-funded by the DELWP and the Bureau. A review of the scientific literature around baselines done under the project has found limited prior research into this question. The research will assess whether a more robust approach to defining the baseline can be developed. We are analyzing baselines over the historical period and for coming years and decades to examine the impact of natural climate variability and anthropogenic forcing on the baselines. We present results on baselines in both the observations and a large number of climate models from around the world.



Time series of the observed mean cool season (April-October) rainfall (grey color) and the 10-year running mean (black color) in mm month^{-1} over Victoria, Australia. The horizontal dashed and dotted black lines represent the different baselines periods recommended by WMO (i.e. 1961-1990 and 1981-2010). The blue dashed line represents the baseline (1975-current) recommended by DELWP, the green dashed line is the baseline (1986-2005) used in IPCC AR5 reports while the red dashed line represent the baseline from the start of Millennium Drought to current (1997- current).

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IMPACT OF GLOBAL WARMING ON ENSO-DRIVEN RAINFALL VARIABILITY IN THE PACIFIC

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Introduction

The El Niño–Southern Oscillation (ENSO) drives substantial variability in rainfall, severe weather, agriculture, and ecosystems in many parts of the world. Although this issue has been investigated many times over the past 20 years, there is very little consensus on future changes in ENSO, apart from an expectation that ENSO will continue to be a dominant source of year-to-year variability. Here we show that there are in fact robust projected changes in the spatial patterns of year-to-year ENSO-driven variability in both surface temperature and precipitation. We present results from the Coupled Model Intercomparison Project versions 3 and 5 (CMIP3 and CMIP5) coupled model ensembles, as well as from experiments conducted using the ACCESS atmospheric general circulation model (AGCM), showing a nonlinear precipitation response to warmer sea surface temperatures (SSTs).

Methods and Summary of Results

To investigate projected changes in precipitation, we analysed four different twenty-first-century emission scenarios are presented (RCP8.5, RCP4.5 and 1% CO_2 from CMIP5, and SRES A2 from CMIP5). Fig 1a,c,e,g shows that even though there is a large disagreement amongst models on how ENSO-driven SST variability will change in the 21st century, the models exhibit a greater degree of agreement on how ENSO-driven precipitation will change (Fig 1b,d,f,h).

We also conducted a suite of AGCM experiments using ACCESS 1.0 investigating how ENSO-driven precipitation changes in response to a warmer mean state only, without any changes in ENSO-driven SST variability. We applied El Niño and La Niña SST anomalies of varying strengths (1-4 times the observed composite anomalies). Under 20th century conditions, we found a strong nonlinear precipitation response to El Niño SST anomalies, with precipitation increasing across the central and eastern equatorial Pacific. This nonlinear response is enhanced under 21st century conditions (warmer SSTs and increased CO_2; Fig 2a). For La Niña, there is a weaker, though still nonlinear response to imposed SST anomalies, in which precipitation decreases along the central equatorial Pacific. Contrary to the El Niño case, the response to La Niña SST anomalies is weaker under 21st century conditions (Fig 2b). Additional experiments were run using observed time-varying SSTs, with and without an added SST warming pattern (Fig 2c), with the precipitation response to global warming showing good agreement with coupled model projections of precipitation change.

To understand the causes of the precipitation responses from the AGCM, a moisture budget analysis was performed. The precipitation response to El Niño and La Niña was found to be dominated by changes in the atmospheric mean circulation dynamics. The response to global warming was found to be a balance between dynamic and thermodynamic changes during El Niño years, and dominated by thermodynamic changes during La Niña years.

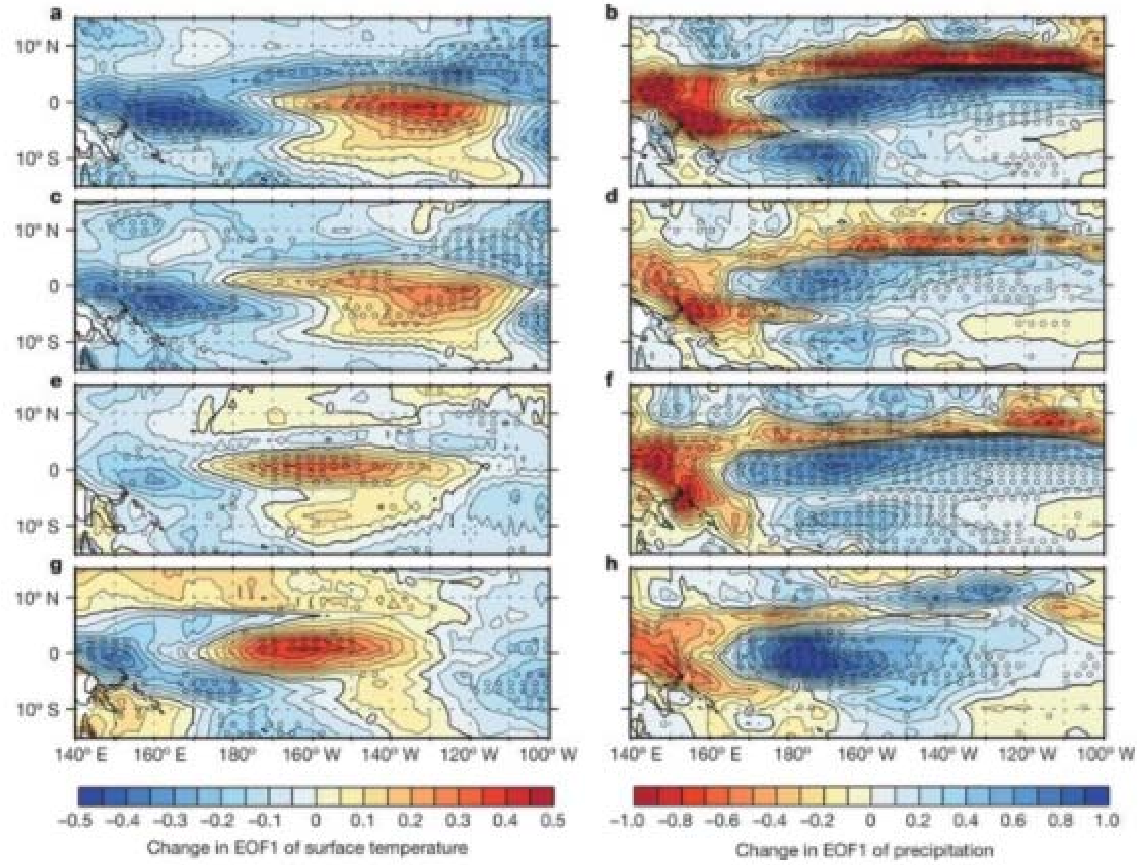

Figure 1: Multi-model average (MMA) of the projected change in the structure of the standardized first EOF of interannual (high-pass-filtered, 'year-to-year') variability for the four twenty-first-century scenarios. a, c, e, g, Surface temperature (ST); b, d, f, h, precipitation. The pattern for each model was standardized by the spatial standard deviation of EOF1 over the domain 0–360° E, 30° S to 30° N. The CMIP5 models were forced using RCP8.5 (a, b), RCP4.5 (c, d) and 1% CO_2 (e, f). The CMIP3 models were forced using SRES A2 (g, h). Stippling indicates that more than 70% of models agree on the sign of change. Red shades indicate an increase in EOF1 (ST) and a decrease in EOF1 (precipitation).

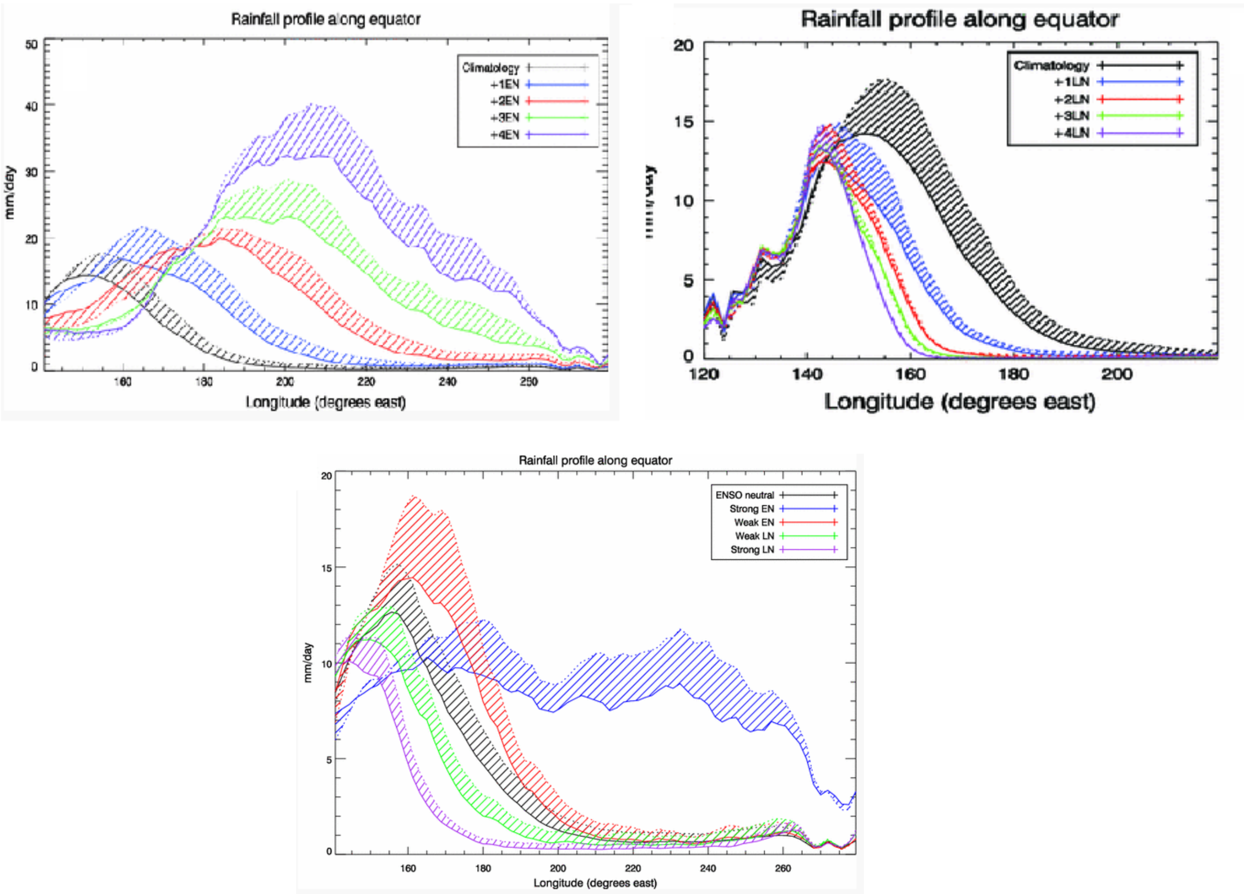

Fig 2: Rainfall profiles along the equator for (a) imposed El Niño SST anomalies (1-4 times observed composite), (b) imposed La Niña SST anomalies (1-4 times observed composite), and (c) imposed time-varying SSTs (1951-2010). *Thick solid lines*represent the 20C runs, and *dotted lines* represent the 21C runs. The areas between the 21C and 20C runs are stippled to highlight the precipitation changes.

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IMPACT OF GLOBAL WARMING ON ENSO TELECONNECTIONS

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In an earlier presentation we described evidence from CMIP5 climate models that El Niño-Southern Oscillation (ENSO)-driven precipitation variability in the equatorial Pacific is projected to increase during the 21st century in response to business-as-usual increases in greenhouse gas concentrations. In this presentation we will examine some of the implications of this increase as reported by Power et al. (2017) and Power and Delage (2018). We will describe the most comprehensive study to date on the influence of global warming on the impact of ENSO on rainfall around the world. The study, which took several years to complete, is based on projected changes in climatic conditions during El Niño years and in ENSO-driven precipitation variability in 36 CMIP5 climate models from around the world. The models are forced according to the RCP8.5 scenario in which there are large, unmitigated increases in greenhouse gas concentrations during the twenty-first century (RCP8.5).

Under this scenario ENSO precipitation variability is projected to increase in many locations, about long-term average conditions that will generally be very different from those experienced in the past, if global greenhouse gas emissions continue to rise. ENSO-driven precipitation variability is projected to increase by around 15%–20% of the level of variability experienced during the 20th century in many locations.

The situation in Australasia is a little different: while long-term average drying is projected during winter in southern Australasia, ENSO-driven variability about this drier average is projected to remain roughly the same as it was last century. This means that winter rainfall during El Niño years, for example, will tend to be lower that it was last century, because of long-term average drying, not because the impact of El Niño on southern Australasia increases.

In the second study (Power et al. 2017) we will show that the disruption to Pacific rainfall patterns that ENSO in CMIP5 climate models causes will become more frequent even if large and sustained cuts to global greenhouse gas emissions are implemented. In the models the risk of major disruption was already inflated by the end of the 20th century. This suggests, for example, that the major El Niño events of 1982/83 and 1997/98, may have been rendered more disruptive by greenhouse gas emissions since the industrial revolution began than they would have been without the preceding those emissions. These points are illustrated in Figure 2.

Climate models are not able to perfectly simulate the properties of ENSO. It will therefore be interesting to see how ENSO in the next generation of climate models - as they emerge over the next few years - respond to global warming.

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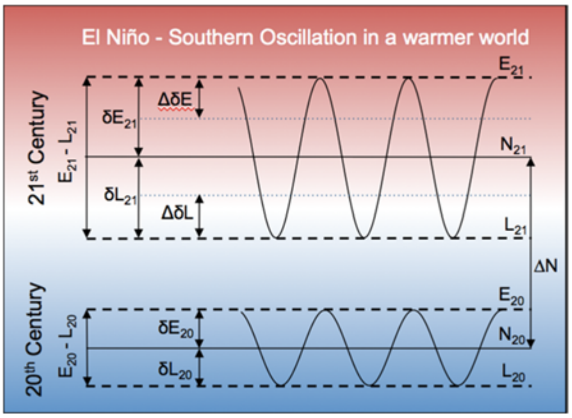

Figure 1: Schematic showing that precipitation during future El Niño (E) and La Niña (L) years can depend on changes to ENSO-driven variability, as well as changes in precipitation during neutral years (N).

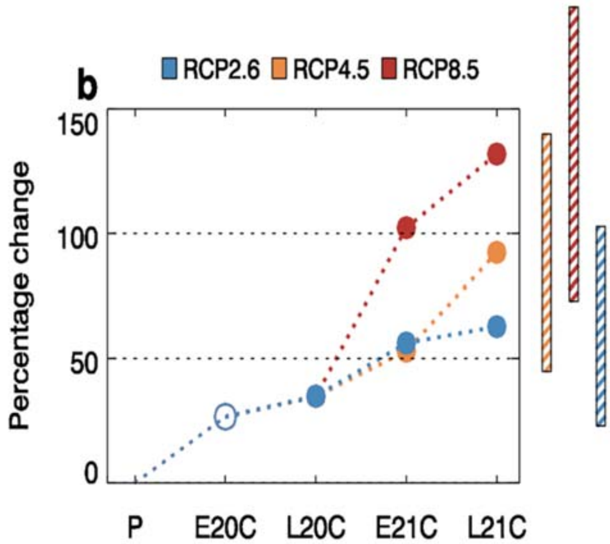

Figure 2: Percentage change in the frequency of major disruptions to Pacific rainfall in the 20th and 21st Centuries. Early 20th Century (E20C), late 20th century (L20C), early 21st century (E21C) and late 21st century (L21C) frequency changes relative to the pre-industrial period, for three different scenarios: RCP2.6 (blue), RCP4.5 (orange) and RCP8.5 (red). The results are based on changes obtained from 20 CMIP5 climate models that were forced with all three scenarios. Filled circles indicates statistical significance at 90% level. Bars indicate the 90% confidence interval of the multi-model mean (MMM) change for L21C.

USING ENSEMBLES IN CLIMATE SENSITIVITY AND FEEDBACKS

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Climate sensitivity represents the amount of warming that would be experienced for a standard increase (doubling) of atmospheric CO_2. It is closely linked to the actual warming that is seen globally and over Australia, and therefore is central to the magnitude of projected climate change. Consequently, the climate science community has put large, repeated, and ongoing efforts into estimating climate sensitivity. For example, each subsequent Intergovernmental Panel on Climate Change (IPCC) Assessment report has made formal climate sensitivity estimates, which typically feature as 'headline' statements of the reports. However, over roughly four decades the evaluated 'likely' range of this parameter has not contracted. The recent IPCC AR5 (2013) concluded that this range is 1.5 to 4K, identical to the 'Charney Report' from 1979 (National Research Council, 1979). Why is this range so large, how is it estimated, and what role do ensembles play in its estimation?

The evaluation of climate sensitivity can be considered the *poster child* of the use of ensembles in climate change science, as it represents one of the most important single quantities in climate science, and because it is based on an *ensemble of ensembles*. In the AR5 (see Fig. 1) the final evaluation was based on a meta-ensemble of estimates from (i) the instrumental record, (ii) climatological constraints, (iii) raw model ranges and (iv) paleoclimate estimates. In turn most of these were ensemble based. For example, the climate model ranges came from the large CMIP3 and CMIP5 multi-GCM ensembles, along with perturbed physics ensembles based on several individual models. The amalgamation of these ensembles into a meta-ensemble, along with 'expert judgement', formed the basis of the final assessment.

This paper will discuss the different methodologies used in these ensembles and give some indication of their strengths and weaknesses. It will also discuss how the use of ensembles not only provides an estimated range but can cast light on critical aspects of sensitivity and the underlying climate radiative feedbacks that are responsible for the range. For example, ensembles show inter-relationships between different feedbacks, clarify the sources of confidence/uncertainty and suggest potential observational constraints. One such example that will be discussed is how ensembles can explore relationships between critical feedback processes operating under climate change, and similar processes operating under interannual and decadal variability (Colman and Power, 2018). These in turn hold out the hope for constraining climate sensitivity from past or future measurements of variability.

Finally, look to the future, and explain how ensembles in the upcoming CMIP6 are designed to help narrow uncertainties in feedbacks and climate sensitivity, and therefore the magnitude of expected future climate change.

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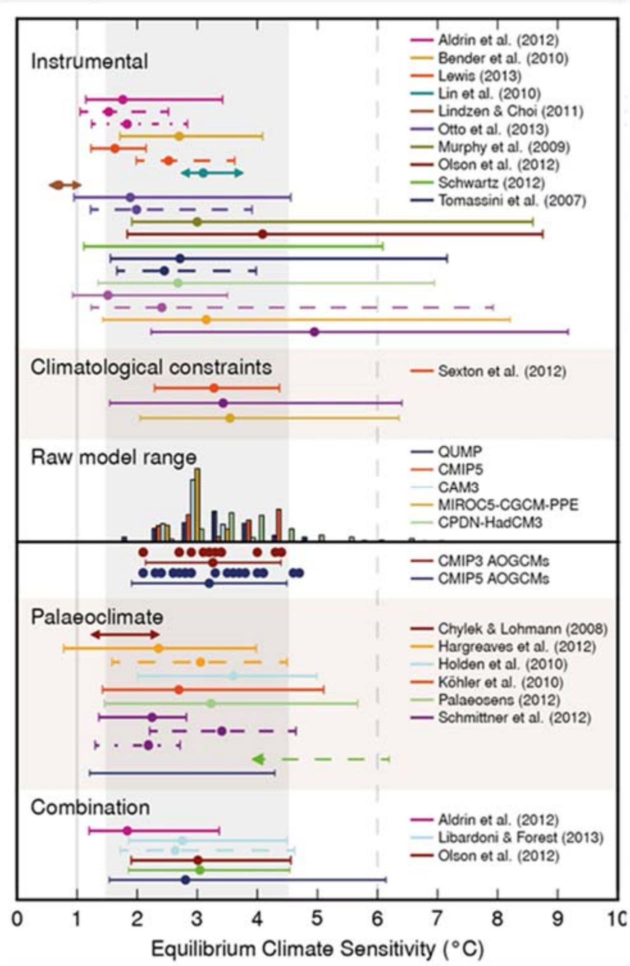

Figure 1: Probability density functions, distributions and ranges for equilibrium climate sensitivity, plus climatological constraints shown in IPCC AR4, and results from CMIP5. The grey shaded range marks the likely 1.5°C to 4.5°C range, and the grey solid line the extremely unlikely less than 1°C, the grey dashed line the very unlikely greater than 6°C. Source: IPCC AR5 (2013) Box 12.2, Figure 1.