Climate Risk Early Warning System for Island Nations: Tropical Cyclones

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Abstract

Tropical cyclones (TCs) frequently affect coastal areas of Australia and islands in the tropical Indian and Pacific oceans. Multi-hazards associated with TCs (destructive winds, storm surges and torrential rain) have dramatic impact on population and infrastructure. Accurate forecasting of TC seasonal activity is an important part of a Climate Risk Early Warning System (CREWS) for improving resilience of the society to potentially destructive impacts of TCs. Currently, a statistical model-based prediction of TC activity in the coming season is used for operational seasonal forecasting in the Australian region and the South Pacific Ocean. In this chapter, a possibility of improving the accuracy of seasonal TC prediction using advanced statistical model-based approaches is demonstrated. It is also demonstrated that an alternative approach—dynamical (physics-based) climate modelling—is promising for skilful seasonal TC forecasting. Using improved statistical and dynamical model-based methodologies for TC seasonal prediction as an integral part of the CREWS will provide valuable information about TC seasonal variability and will assist with decision making, responses and adaptation in island countries.

Keywords: tropical cyclones, early warning system, multi-hazards, preparedness

1. Introduction

Tropical cyclones (TCs) frequently affect coastal communities of Australia and island nations in the Indian and Pacific oceans, and pose significant threat to life and property. In many cases TC impacts on island countries were devastating [1]. Knowledge about TC variability (spatial and temporal) is important for improving preparedness and resource mobilisation well in advance of potential TC impacts, to reduce risk of multi-hazards associated with TCs.

TC activity is affected by climate variability and climate change. Large-scale climatic modes such as the El Niño-Southern Oscillation (ENSO) are known to modulate TC occurrences [2]. In addition, modelling of future climate suggests likely changes in TC activity. As stated in Chapter 14, Climate Phenomena and their Relevance for Future Climate Change of the IPCC Fifth assessment report: 'Based on process understanding and agreement in twenty-first century projections, it is *likely* that the global frequency of occurrence of tropical cyclones will either decrease or remain essentially unchanged, concurrent with a *likely* increase in both global mean tropical cyclone maximum wind speed and precipitation rates' [3].

To improve our knowledge about historical TCs in the Indian and Pacific oceans and develop accurate methodologies for TC seasonal forecasting, 'Climate Change and Southern Hemisphere Tropical Cyclones' International Initiative has been established in 1999 [4]. This International Initiative addressed three key areas: (i) preparing high quality TC historical database, (ii) producing TC climatology and (iii) developing skilful methodologies for TC seasonal prediction.

TC seasonal forecasting is one of the important elements of a Climate Risk Early Warning System (CREWS) aiming to increase preparedness of coastal communities at risk. Over the last few decades, statistical model-based methods for TC seasonal forecasting have been developed, starting with the pioneering work of Gray [5]. Statistical models are based on historical relationships of TC activity with large-scale environmental drivers which modulate TC activity such as the ENSO. Relating the observed numbers of TCs with ENSO indices it is possible to derive linear regression equations which can be used for prediction of future cyclone activity. The TC-ENSO relationship was used in developing statistical methodology for forecasting seasonal TC activity in the Australian and some other regions [6–8].

However, in a globally warming environment, statistical models may not produce reliable outcomes when values of ENSO indices are outside of the range of historical records. While the developed statistical models performed reasonably well in the past, during a very strong La Niña event in 2010–2011 the statistical models significantly over-predicted the number of TCs in the Australian region [9]. It became evident that improving statistical methodologies and developing new dynamical climate model-based methodologies is essential to improve prediction skill.

In this chapter, prospects for improving the skill of operational seasonal prediction of TC activity in the regions of the Southern Hemisphere (SH) using statistical and dynamical model-based approaches are presented.

2. Southern Hemisphere tropical cyclone archive and data portal

2.1. Tropical cyclone historical data archive

Accurate historical cyclone records (preferably long-term records covering a few decades) are required for reliable prediction of future TC activity. Thus, the first objective of the 'Climate Change and Southern Hemisphere Tropical Cyclones' International Initiative was to prepare a high quality historical database of occurrences of TCs in the Indian and Pacific oceans. Historical TC records have been significantly improved since the 1970s due to availability of satellite imagery [10–12] and they were extensively used for preparing the Southern Hemisphere (SH) TC archive.

The SH TC archive has been prepared at the National Climate Centre (NCC) of the Australian Bureau of Meteorology during 1999–2003 in collaboration with the National Meteorological and Hydrological Services (NMHSs) of Fiji, France and New Zealand (NZ). The first version of the SH TC archive has been released in 2003 [13]. Since then, historical data are regularly updated to keep the archive up to date.

Updating the archive is a two-step procedure which includes (i) collection of best track data (or operational data if best track data are not available) from Tropical Cyclone Warning Centres (TCWCs) in Brisbane, Darwin and Perth (Australia), Jakarta (Indonesia), Port Moresby (PNG), Wellington (NZ), Regional Specialised Meteorological Centres (RSMCs) La Reunion (France) and Nadi (Fiji) and (ii) combining the data in one consolidated archive including quality control, correction for errors and making a consensus expert decision when joining tracks of systems which occurred in two or three areas of responsibilities of different TCWCs and RSMCs.

Recently, as a part of the Pacific Australia Climate Change Science and Adaptation Planning (PACCSAP) program's 'Seasonal tropical cyclone prediction' project, the SH TC archive has been revised. Specifically, data for 1969–1970 to 2010–2011 TC seasons covering the South Pacific Ocean and produced by RSMC Nadi (Fiji), TCWCs Brisbane and Darwin (Australia) and TCWC Wellington (New Zealand) have been examined to eliminate errors and inconsistencies. The following rules have been applied when preparing a consolidated archive. As RSMC Nadi (Fiji) is a designated by the World Meteorological Organization (WMO) centre with responsibilities to issue TC warnings and prepare best track data for the area between the equator and 25°S, 160°E and 120°W, its data have been treated as a primary source of information for this area. However, RSMC Nadi was established in 1995 while the SH TC archive extends to cover TC seasons from the 1970s (satellite era). Thus, TC best track data prepared for this area by TCWCs in Brisbane, Darwin and Wellington have been used for 1969–1970 to 1994–1995 TC seasons, and data from RSMC Nadi—from the 1995–1996 TC season onwards. As for the other areas of the South Pacific Ocean, TC best track data from TCWCs in Brisbane and Darwin for the Australian region (between the equator and 37°S, 135°E and 160°E) and from TCWC Wellington for the New Zealand region (between 25°S and 40°S, 160°E and 120°W) have been used for entire length of records from 1969–1970 to 2010–2011 TC seasons.

As a result of growth of the 'Climate Change and Southern Hemisphere Tropical Cyclones' International Initiative and its geographic expansion to cover the Western North Pacific region, TC best track data produced by RSMC Tokyo for 1977–2011 seasons have been added to the consolidated archive. Similarly, TC best track data produced by RSMC la Réunion for 1969–2011 have been added to cover the South Indian Ocean region.

2.2. Tropical cyclone data portal

Tropical cyclone data portal has been created with aims (i) to visualise the data from the SH TC archive and (ii) allow users to perform analysis of historical cyclone data. Based on recent changes of and additions to the SH TC archive, the TC historical data portal has been re-designed to incorporate best track data for the Western Pacific both south and north of the equator and the South Indian Ocean (**Figure 1**).

Cyclone tracks - Southern Hemisphere [beta]

This is a product developed as part of the Pacific Climate Change Science Program

Tip: Click on a cyclone to find more about it!

Cyclone tracks - Western North Pacific [beta]

This is a product developed as part of the Pacific Climate Change Science Program

Tip: Try selecting a range of seasons

Figure 1. Front page of the portal – the Southern Hemisphere (top panel) and the Western North Pacific (bottom panel).

New functionality has been also added to the portal including enhanced spatial and temporal selection of cyclones. Some examples of the portal's new functionality are given below. The portals are extensively used by NMHSs of island countries in the Pacific and Indian oceans for analysis of historical TC data and consequently it is reflected in the examples.

Analysis of historical TC tracks is often required to examine an individual cyclone's impact on a specific location. Such analysis could be performed using 'Place name' and 'Coordinates' options of the portal (**Figures 2** and **3**, respectively).

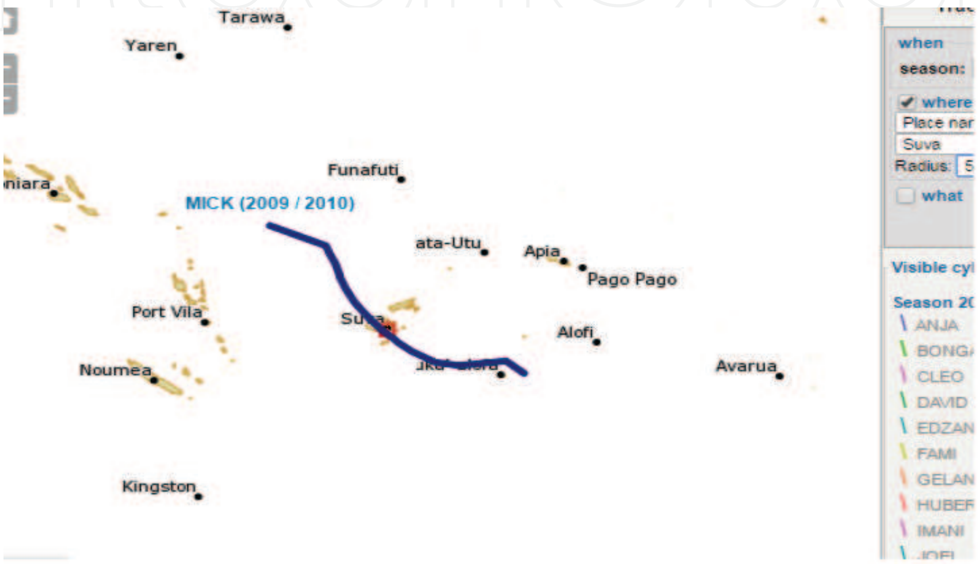

Figure 2. Track of TC *Mick* affecting Suva, Fiji displayed after selecting 'Place name' option.

Figure 3. Track of TC *Bingiza* affecting area within 100 km radius of Antananarivo, Madagascar displayed after selecting 'Coordinates' option.

Similarly, analysis of historical TC tracks is often required to examine occurrences of TCs over larger areas, e.g. an exclusive economic zone of an island country, during a specific season or a number of seasons (**Figures 4** and **5**, respectively).

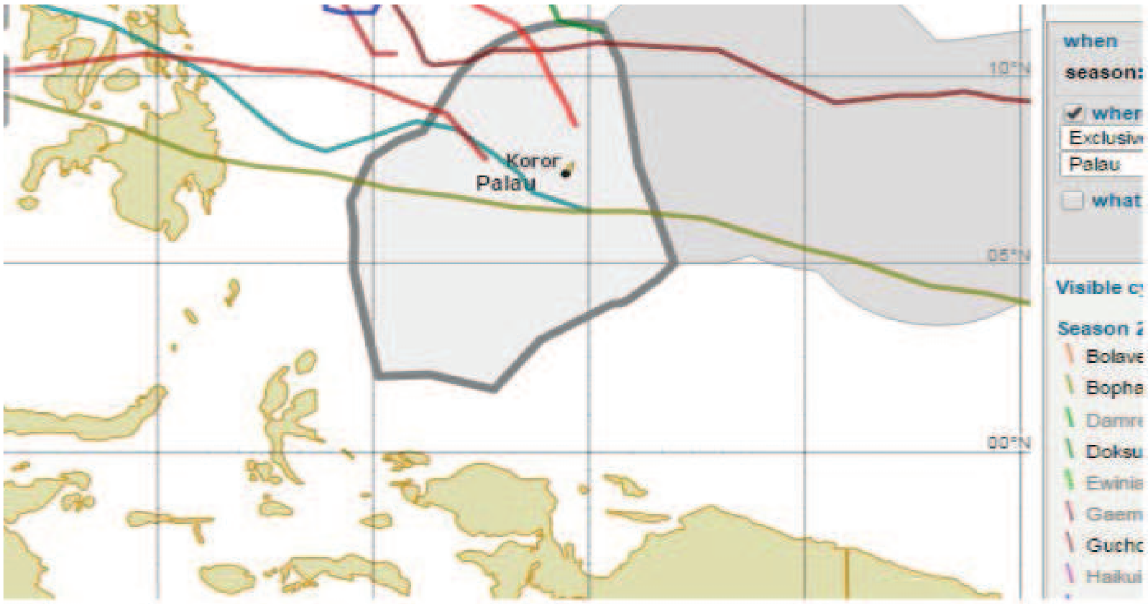

Figure 4. Tracks of TCs which passed through an exclusive economic zone of Palau during 2012 season.

Figure 5. Track of TCs which passed through an exclusive economic zone of Cook Islands from 2008/2009 to 2010/2011 seasons.

Information about cyclone's occurrence (**Figure 6**) and changes of its intensity (**Figure 7**) is also incorporated in functionality of the portal.

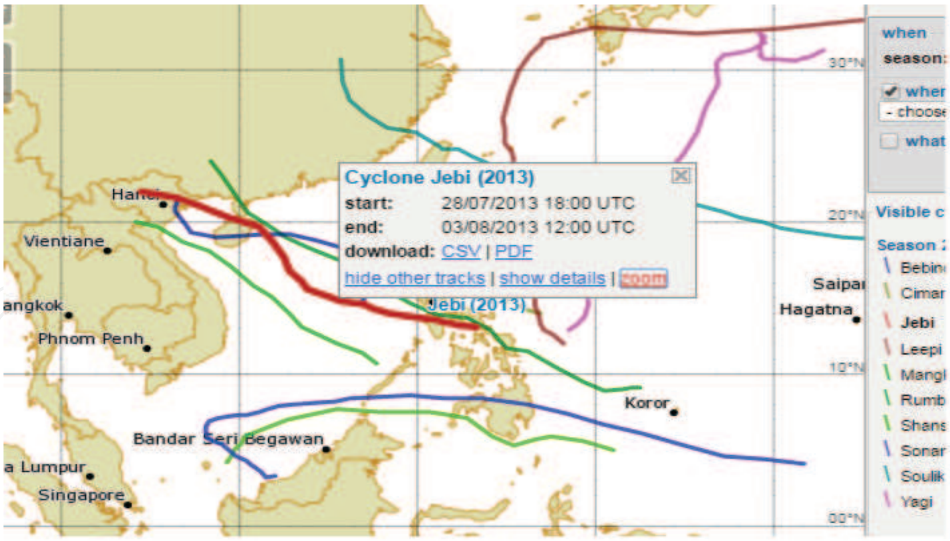
Cyclone Jebi (2013)
start: 28/07/2013 18:00 UTC
end: 03/08/2013 12:00 UTC
download: CSV | PDF
hide other tracks | show details | zoom

Figure 6. Tracks of TCs over selected area in the Western North Pacific in 2013 season together with information about start and end of TC *Jebi*.

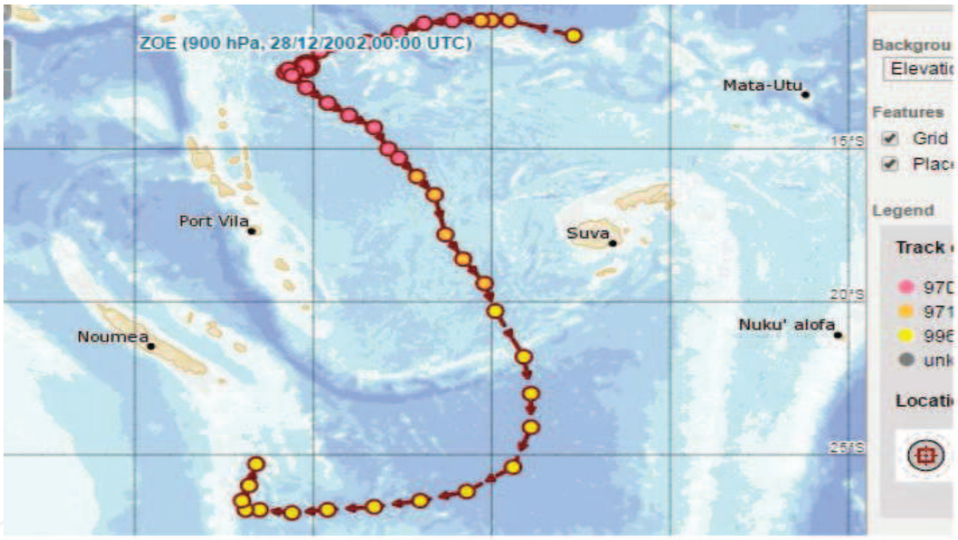

Figure 7. Track of TC *Zoe* displayed over 'Elevation and Bathymetry' background. Changes in the cyclone's intensity are colour-coded; legend is displayed on the right side.

3. Statistical prediction models

Currently, a statistical technique is used by the Australian Bureau of Meteorology to prepare operational TC seasonal prediction for the Australian and the South Pacific Ocean regions. The operational statistical model consists of linear discriminant analysis (LDA) models, based on ENSO indices as predictors.

3.1. The ENSO indices and linear discriminant analysis model

The Southern Oscillation Index (SOI) and sea surface temperature anomalies (SSTAs) in Niño3.4 and Niño4 regions (NIÑO3.4 and NIÑO4) are commonly used indices in defining ENSO phases which describe oceanic and atmospheric responses, respectively.

It has been demonstrated by Kuleshov et al. [2, 7] and Ramsay et al. [14] that in the Australian region a strong correlation (about −0.7) exists between the annual number of TCs and the NIÑO4 and NIÑO3.4 indices averaged over 3 months preceding the onset of a Southern Hemisphere TC season (August-September-October). In the eastern South Pacific Ocean, better correlation of the annual TC number with ENSO indices was found for the NIÑO3.4 and the SOI [7]. Based on these findings, the NIÑO3.4 and the SOI indices have been selected by the Australian Bureau of Meteorology for use in operational LDA statistical TC-ENSO model for seasonal prediction of TCs in both the Australian and the South Pacific regions.

A multivariate ENSO index has been developed at the NCC with the aim to integrate both atmospheric and oceanic responses in one index [2]. It is based on the first principal component of monthly Darwin mean sea level pressure (MSLP), Tahiti MSLP and the NIÑO3, NIÑO3.4 and NIÑO4 SST indices [2, 7]. This standardised monthly anomaly index is usually denoted as the 5VAR index. Further examining correlation of ENSO indices with TC occurrences in the Australian region, Kuleshov et al. [15] found that the 5VAR performs better than the SOI and NIÑO3.4 demonstrating the strongest monthly (−0.67, pre-season September), bi-monthly (−0.67, August and September) and tri-monthly correlation (−0.66, July, August and September).

Incorporating into statistical model a decreasing trend in TC activity over the Australian region in recent years [2, 16] and using 5VAR, SOI and NIÑO3.4 indices as predictors, Kuleshov et al. [15] demonstrated potential for improving skill of the LDA operational model. Brief description of the developed statistical model is presented in the Appendix. Cross-validation employed to assess the models' performance demonstrated that the models which used the pre-season July-August-September SOI and September 5VAR indices and the time trend as the predictors [15] demonstrated increased skill in TC seasonal forecasting compared with currently used LDA model [7].

3.2. Support vector regression (SVR) models

Recently, application of advanced statistical methodologies for seasonal prediction of TCs has been explored. It has been demonstrated that improvement in prediction skill compared to the LDA model can be achieved using support vector regression (SVR) models, exploring new environmental indicators and non-linear relationships between them [9]. Detailed description of the developed SVR models for the Australian and South Pacific Ocean regions could be found in [17] and its brief description is presented in the Appendix. Analysis of the results of the SVR models shows that the Dipole Mode Index, the 5VAR index and the SOI are the most frequently used indices selected for TC seasonal forecasting in the Australian and South Pacific regions.

4. Dynamical climate models

Dynamical climate modelling is an alternative to statistical modelling. Early analysis has revealed that the dynamical seasonal prediction system Predictive Ocean Atmosphere Model for Australia (POAMA) has skill in the prediction of ENSO which modulates TC activity in the SH [2].

As a part of the 'Climate Change and Southern Hemisphere Tropical Cyclones' International Initiative, an evaluation of performance of dynamical climate models for TC seasonal prediction was conducted under the PACCSAP program. The Australian Bureau of Meteorology and the Japan Meteorological Agency/Meteorological Research Institute (JMA/MRI) have developed systems to provide predictions of TC activity based on their dynamical models.

The two agencies each have their own coupled seasonal forecast model comprised of a number of ensemble members and a 30-year hindcast period. The JMA/MRI-CGCM is used by the JMA/MRI; the Bureau uses POAMA. Each agency has employed a different TC identification and tracking procedure to determine the number of TCs produced by their model within each ensemble member in each year of the hindcast.

In this section, the ability of each model to produce an environment consistent with observations is examined in the context of environmental parameters related to TC genesis. The TC tracking methods are presented and their performance when applied to the respective model hindcast ensembles is evaluated.

4.1. A comparison of dynamical seasonal tropical cyclone predictions for the Australian and Western Pacific regions

4.1.1. TC tracking in POAMA

Dynamical model POAMA [18] is comprised of 30-member ensemble and 31-year hindcast (1980–2010). Realisations initialised on 1 October each year (i.e. prior to start of the Southern Hemisphere TC season) are used to evaluate model's performance. Each realisation provides 9 months of daily global atmospheric environmental fields at approximately 2.5° × 2.5° resolution.

TCs are identified and tracked using 'Okubo-Weiss-Zeta Parameter' (OWZP) scheme [19]. In brief, regions of low deformation vorticity (large OWZP) at 850- and 500-hPa levels which are vertically coherent and are sustained for an appreciable duration (at least 48 hours) are identified. Where such regions occur in presence of small vertical wind shear and large lower tropospheric humidity, local environment is considered conducive to imminent TC genesis or TC maintenance.

OWZP scheme is applied to 9-month daily POAMA data for each ensemble member and year individually. Statistics for TC-like disturbances for each member are then averaged together to give ensemble mean statistics for each year.

4.1.2. TC tracking in JMA/MRI-CGCM

The seasonal JMA/MRI-CGCM [20] is comprised of a 10-member ensemble, and the same 31-year hindcast period as POAMA is utilised in this analysis. The realisation for the forecast period beginning 1 November each year is used; each realisation provides daily global atmospheric environmental fields covering the November-April period at approximately 1.875° × 1.875° resolution.

TCs are identified and tracked using a method similar to that outlined by [21], whereby grid points with 850 hPa relative vorticity less than a threshold value are identified and the sea-level pressure minimum within the surrounding grid points is denoted as the centre of the possible TC. A warm-core is required of these possible TCs: the thickness between 500 and 200 hPa must exceed that of the local environment, and wind speed at 850 hPa must be greater than that at 200 hPa. A full description of this method can be found in [22].

For a possible TC to be considered, it must last longer than 2 days and be equatorward of 30°S.

This scheme is applied to daily JMA/MRI-CGCM data for the November-April period for each ensemble member and year individually. Statistics for TC-like disturbances for each member are then averaged together to give ensemble mean statistics for each year.

The TC identification and tracking method is basin dependent. The method is applied to the global atmospheric fields using a variety of 850 hPa relative vorticity thresholds. For each basin, the observed climatological number of TCs is compared to the ensemble mean hindcast climatological value for each low-level vorticity threshold; the closest value is then selected for each basin.

4.2. Model environment

The ability of the models to represent the large-scale environment in which the TCs form has been demonstrated for 850 hPa relative vorticity vertical and troposphere-deep (850–200 hPa) vertical wind shear [23]. The results discussed here use a threshold value of $4.5 \times 10^{-5}\ s^{-1}$ for the Australian region and $7.5 \times 10^{-5}\ s^{-1}$ for the South Pacific region.

During November-December-January (NDJ), both models realistically capture the variability in low-level vorticity near the equator in the western Pacific with correlation values exceeding 0.8 is places. In the tropical Australian region the models do much less well.

The model drift associated with longer lead times is clearly evident in the February-March-April (FMA) season plots, with correlation values of low-level vorticity reduced from NDJ for both models.

Similar statements apply for both models in terms of the vertical wind shear.

4.3. Seasonal TC prediction

Ensemble mean variability in the number of TCs in the SH TC season (November-April; NDJFMA) is shown in **Figures 8** and **9**, along with the observed number of TCs from the BoM SH TC dataset [7].

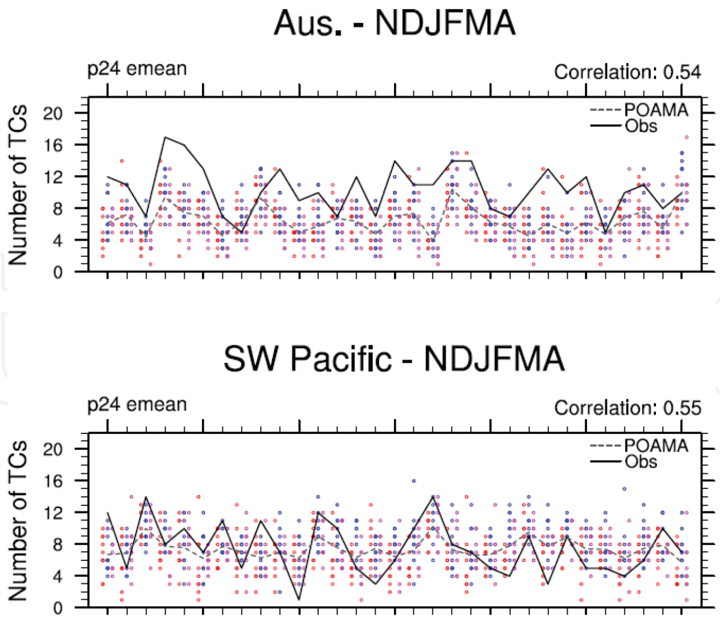

Figure 8. Time series of annual (NDJFMA) number of TCs in POAMA for the Australian (top panel) and South Pacific (bottom panel) regions. TC numbers are shown for observations (solid black line) and ensemble mean (dashed grey line). Ensemble members are shown as coloured circles.

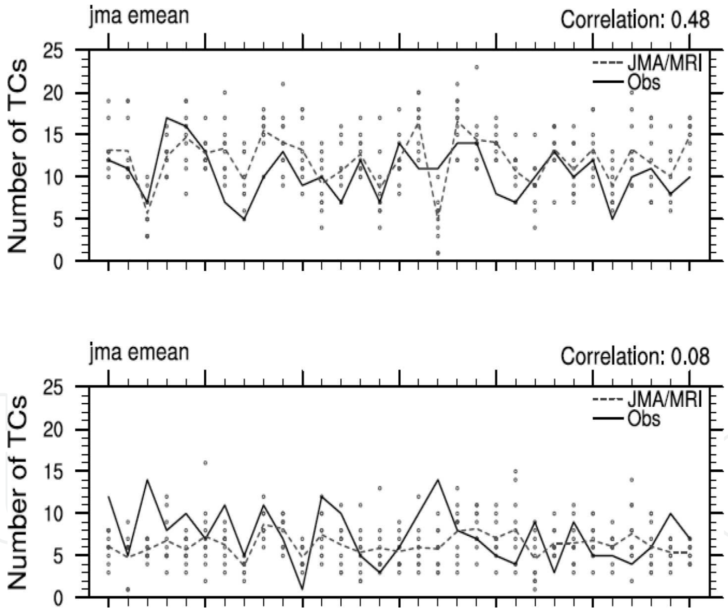

Figure 9. Time series of annual (NDJFMA) number of TCs in JMA/MRI-CGCM for the Australian (top panel) and South Pacific (bottom panel) regions. TC numbers are shown for observations (solid black line) and ensemble mean (dashed grey line). Ensemble members are shown as grey circles.

In the Australian region POAMA underestimates the number of TCs throughout the hindcast period, suggesting a deficiency in the model's ability to produce TC-like disturbances in this region. This is not the case in the western South Pacific. In both basins, some of the inter-annual variability is captured by POAMA, yielding a correlation values with observations of ~0.55.

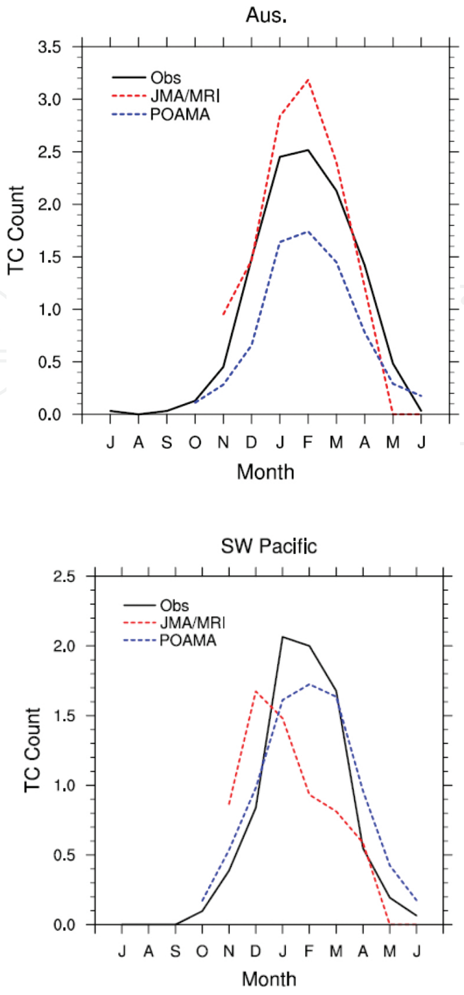

Figure 10. Climatological number of TCs as a function of month for observations (solid black line), POAMA (blue dashed line) and JMA/MRI-CGCM (red dashed line) in the Australian (top panel) and South Pacific Ocean (bottom panel) regions.

By design JMA/MRI-CGCM yields annual totals of TCs for NDJFMA close to climatology for both basins and in the Australian region a similar degree of variability to POAMA is captured, demonstrated by a correlation value of 0.48. In the South Pacific JMA/MRI-CGCM fairs less well at capturing the variability.

Ensemble mean monthly TC climatologies for each basin and model are shown compared with observations in **Figure 10**.

Both models capture the monthly variability in the Australian region well, although neither model represents the peak value correctly. In the South Pacific, POAMA performs well, however, JMA/MRI-CGCM peaks a month too early and drops off too quickly.

In summary, POAMA and JMA/MRI-CGCM both represent the large-scale environment relevant to TCs reasonably well, although possible deficiencies exist in the Australian region. The monthly TC climatologies in both models are reasonably realistic. Both models capture some of the inter-annual variability in the Australian region, although POAMA performs better in the South Pacific. Probabilistic NDJFMA TC number predictions both models, evaluated over the 31-year hindcast, show skill over random chance.

With further development of dynamical climate models and improving of their skill it is expected that both statistical and dynamical models will be used in operational TC seasonal prediction in the Australian and South Pacific regions, to complement each other.

5. Conclusions

Historically, multi-hazards associated with TCs (destructive winds, storm surges, torrential rain and related flash-flooding) had significant impacts on population and coastal infrastructure of Australia and island countries of the Indian and Pacific oceans. Improved forecasting of TC seasonal activity is an important part of the Climate Risk Early Warning System (CREWS) for improving resilience of the society to potentially destructive impacts of TCs. Currently, a statistical model-based prediction of TC activity in the coming season is used for operational seasonal forecasting in the Australian region and the South Pacific Ocean by the Australian Bureau of Meteorology, the National Institute for Water and Atmospheric Research (NIWA) in New Zealand and the Guy Carpenter Asia-Pacific Climate Impact Centre (GCACIC) at the City University of Hong Kong.

In this chapter, a possibility of improving the accuracy of TC seasonal forecasting using advanced statistical model-based approach (e.g. support vector regression methodology) was demonstrated. Moreover, it was shown that dynamical (physics-based) climate models have potential for skilful seasonal TC forecasting. Transition from a statistical to a dynamical prediction system will ultimately provide more valuable and applicable climate information about TC seasonal variability, which can inform decision making, responses and adaptation in Australia and Pacific and Indian Ocean island countries.

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Appendix: Brief description of the developed statistical models

A. Linear discriminant analysis (LDA) model

Linear discriminant analysis (LDA) model is currently used as an operational model for TC seasonal prediction by a number of organisations including the Australian Bureau of Meteorology which utilise NIÑO3 and SOI indices as LDA models' inputs [7]. Examining prospects for improving skill of operational TC seasonal forecasting, Kuleshov et al. [15] demonstrated that 5VAR index performs better than NIÑO3 and SOI. Consequently, the LDA model for annual total occurrences of TCs in the Australian region (AR) has been modified to use 5VAR and also incorporate time trend variable (T) as predictors in the region:

$$AR = \beta_0 + \beta_1 T + \beta_2 5VAR + \epsilon$$

where $\epsilon N(0, 2)$. For a detailed mathematical description of the developed LDA model, see [15].

B. Support sector regression (SVR) model

Support vector regression (SVR) has been identified as a skilful machine learning algorithm for application to TC seasonal prediction [9]. Using non-parametric and non-linear regression approach, annual total number of TCs expected to be formed in the coming season (Y) has been generated using nine variables as the model's input. Selected input variables (X_1–X_9) were the following indices: X_1, Dipole mode index; X_2, NIÑO4; X_3, NIÑO3.4; X_4, NIÑO3; X_5, NIÑO1.2; X_6, El Niño Modoki index; X_7, 5VAR index; X_8, multivariate ENSO index; and X_9, SOI. For a detailed mathematical description of the SVR model, see [17].

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