Seasonal forecasting of tropical storms using the Met Office GloSea5 seasonal forecast system

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The variability and predictability of tropical storm activity in the Met Office fully coupled atmosphere–ocean Global Seasonal Forecast System 5 (GloSea5) is assessed. GloSea5 is a high-resolution seasonal forecast system with an atmospheric horizontal grid of 0.83° longitude × 0.55° latitude (∼53 km at 55°N) and 0.25° in the global ocean. The performance of the system is assessed in terms of its ability to retrospectively predict the observed tropical storm climatology and its response to the El Niño–Southern Oscillation (ENSO). Results are compared to the predecessor system GloSea4 (∼120 km atmospheric horizontal resolution) and observational analyses over the common period of the operational hindcast for both systems: 1996–2009. A supplementary assessment of GloSea5 for the period 1992–2013 is then performed to evaluate skill of tropical storm predictions in the Northern Hemisphere as well as landfall frequency along two regions, the US coast and the Caribbean, over a longer period. GloSea5 is able to reproduce key tropical storm characteristics, such as their geographical distribution, seasonal cycle and interannual variability, as well as spatial changes in storm track density with ENSO. GloSea5 shows statistically significant skill for predictions of tropical storm numbers and accumulated cyclone energy (ACE) index in the North Atlantic, western Pacific, Australian region and South Pacific. Statistically significant skill is also found for predictions of landfall frequency along the Caribbean coastline. Skill is similar using either the direct counting of landfalling storms in the model, or by inferring landfall rates from the Atlantic basin-wide storm count. We find no skill for predictions of landfall along the US coast. Results suggest the potential for operational seasonal tropical storm forecasts throughout the Tropics.

Key Words: seasonal forecasting; ensembles; tropical storms; landfall

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1. Introduction

Tropical cyclones are amongst the most damaging natural hazards on the planet, causing significant socio-economic impacts. Efforts to predict tropical storm activity on seasonal time-scales started in the late 1970s with methods based on statistical–empirical relationships (e.g. Nicholls, 1979; Gray, 1984b; Chan et al., 1998, 2001). A major assumption of these methods is that the relationships between observed tropical storm activity and precursor climatic predictors, derived from historical records, still hold in the future, which is not always the case (e.g. Klotzbach, 2007; Chan, 2008).

An alternative and relatively new method is to use global climate (or dynamical) models. Dynamical models use the laws of physics and can in principle model nonlinear and non-stationary climate effects. These models are presently used for intra-seasonal (e.g. Vitart et al., 2010), seasonal (e.g. Vitart and Stockdale, 2001; Vitart et al., 2007; Camargo and Barnston, 2009; Vecchi et al., 2011; Villarini and Vecchi, 2013; MacLachlan et al., 2014) and multi-annual (e.g. Smith et al., 2010; Vecchi et al., 2013) tropical storm predictions. On seasonal time-scales, dynamical predictions can be made using a fully coupled atmosphere–ocean model (e.g. Vitart et al., 2007; Molteni et al., 2011; MacLachlan et al., 2014; Vecchi et al., 2014) or an atmosphere-only model.
forced with forecast (e.g. LaRow et al., 2010) or persisted (e.g. Zhao et al., 2010) sea-surface temperature anomalies. ‘Hybrid’ methods (combinations of dynamical model output with statistical methods) are also used (e.g. Vecchi et al., 2011; Villarini and Vecchi, 2013). Vitart et al. (2007) showed that fully coupled dynamical forecasts, particularly when derived from a multi-model combination, have skill at least as high as statistical methods on seasonal time-scales for basin-wide storm counts. These models also show skill for regional predictions of tropical storm activity (e.g. Vitart et al., 2003; Vecchi et al., 2014).

The Met Office has issued forecasts of tropical storm activity using a fully coupled dynamical model for the North Atlantic basin since 2007, and as a multi-model combination with the European Centre for Medium-Range Weather Forecasts (ECMWF) since 2010. These forecasts, for total numbers of named storms, hurricanes (winds of at least 74 mph = 64 kt = 33 m s⁻¹) and accumulated cyclone energy (ACE) index—a measure of the strength and duration of storms during the season—are freely available from the Met Office website.* Despite these advances, predicting landfall remains a challenge. Basin-wide numbers of Atlantic tropical storms explain only a small amount (around 21% from 1966 to 2008) of US hurricane landfall variability and associated losses (Pielke, 2009), thus predictions of landfall based on seasonal forecasts of Atlantic tropical storm numbers are not always skillful. A recent example, as discussed by Vecchi and Villarini (2014), is the 2010 season, which recorded above-normal numbers of tropical storms (19), but only one made landfall in the USA (Bell et al., 2011).

Landfall presents a major challenge for dynamical models, as highlighted in Camargo et al. (2010). The coarse resolution often means that the size of the tropical storm vortices is larger than observed, which could lead to biases in both storm intensity and storm tracks. (There are also other issues simulating tropical storms in low-resolution climate models, which are reviewed by Camargo, 2013). Higher-resolution climate models are better able to simulate the geographic distribution and characteristics of tropical storms (e.g. Sheavitz et al., 2014); however, these have previously been too computationally expensive to run for operational seasonal predictions.

The El Niño–Southern Oscillation (ENSO) is the largest single predictable factor influencing global tropical storm activity on seasonal time-scales, impacting both their frequency and spatial distribution (Camargo et al., 2010). Climate models, both at high and low resolution, are able to simulate the geographic variability of track density with ENSO phase (e.g. Bell et al., 2014; Wang et al., 2014; Sheavitz et al., 2014). Since landfall location and intensity is determined by the storm’s genesis location and track, changes in the spatial distribution of tracks associated with ENSO may lead to changes in risk of landfall (e.g. Camargo et al., 2007b, 2008), which may be predictable on seasonal time-scales.

In this study we investigate this relationship, and analyse results of direct tracking of storms in the Met Office Global Seasonal Forecast System 5 (GloSea5; MacLachlan et al., 2014). Results are compared to the lower-resolution predecessor system GloSea4 (Arribas et al., 2011), ERA-Interim reanalysis and observations.

We structure the article as follows: in section 2 the models, datasets and tracking methodology are described; in section 3 the climatology of tropical storms are presented, including their global distribution, genesis locations, frequency, interannual variability and seasonal cycle. The influence of ENSO on tropical storm distribution is also explored. Finally, predictability of landfall frequency in the US and Caribbean regions are examined. The main conclusions are provided in section 4.

*Met Office tropical cyclones: http://www.metoffice.gov.uk/weather/tropical_cyclone/(accessed 23 January 2015).

2. Models, data and methods

2.1. Models

The Met Office Global Seasonal Forecast System 5 (GloSea5; MacLachlan et al., 2014) is used in this study and compared to the predecessor system GloSea4 (Arribas et al., 2011). Both systems are built around the coupled Met Office Hadley Centre Global Environment Model version 3 (HadGEM3; Hewitt et al., 2011) and use the Met Office Unified Model Global Atmosphere 3.0 scientific configuration (Walters et al., 2011). GloSea5 is the latest version of the Met Office seasonal forecast system with increased horizontal resolution in the atmosphere and ocean compared to GloSea4. GloSea5 has a resolution of 0.83° longitude × 0.55° latitude (N216; ~53 km at 55° N, ~93 km at the Equator) and is coupled to an ocean model with a resolution of 0.25°. In comparison, GloSea4 had an atmospheric horizontal resolution of 1.875° longitude × 1.25° latitude (N96; ~120 km at 55° N, ~208 km at the Equator); the ocean component had a horizontal resolution of 1°, with a refinement at the Equator to 1/3°. Both systems have the same vertical resolution in the atmosphere (85 levels) and the ocean (75 levels) and have 3 hourly atmosphere–ocean coupling.

The performance of the two systems is compared using the operational 1996–2009 hindcasts from two start dates (May and November), with initialisation on three consecutive weeks centred on the first day of the month:

- May (25 April, 1 May and 9 May) to capture the Northern Hemisphere (NH) tropical storm season June–November;
- November (25 October, 1 November and 9 November) to capture the Southern Hemisphere (SH) season November–April.

The hindcast period used for calibration and verification of real-time operational forecasts was set to that of the most recent 14 years (1996–2009) on adoption of the HadGEM3 model (Arribas et al., 2011, give further details). The upgrade to GloSea5 retained the same reference period to facilitate comparison and continuity of products. Nevertheless, for specific studies, extra retrospective runs have been completed (e.g. extension to December–January 1993–2012 from the November start date for assessment of the North Atlantic Oscillation (NAO); Scaife et al., 2014). For the present study, eight additional years with 30 members per year have been run from the May start date to enable further assessment of tropical storm activity for NH basins from 1992 to 2013. Assessment of SH basins using the data in Scaife et al. (2014) was not possible since it did not cover the full tropical storm season (November–April). Thus, a comparison of GloSea4 and GloSea5 is made for the whole globe over the common hindcast period (1996–2009) and an additional assessment of NH tropical storm activity is made for GloSea5 over a longer 22 year period (1992–2013).

The atmosphere and land surface in the hindcasts are initialised using re-analyses from the ECMWF Interim Reanalysis (ERA-Interim; Dee et al., 2011) project. Ensemble members initialised on the same date use identical initial conditions for all model components. Random perturbations are added during the model integration by a physical parametrisation which replaces kinetic energy that has been dissipated. This scheme, Stochastic Kinetic Energy Backscatter (SKEB2), is described in Bowler et al. (2009).

The two forecast systems have a different number of hindcast ensemble members. For GloSea4 only, the operational hindcast of nine ensemble members per year are available for both the May and November start dates. For GloSea5 we have additional hindcast runs: there are a maximum of 30 (minimum of 25) ensemble members per year for the May start and 15 ensemble members per year for the November start. Due to the difference in the number of ensemble members, storm counts are normalised by dividing by ensemble size to make them as directly comparable as possible.
2.2. Observations and reanalysis data

Observational data for the North Atlantic and Eastern Pacific basins are obtained from the National Oceanic and Atmospheric Administration (NOAA) National Hurricane Center’s best-track Hurricane Database (HURDAT2; Landsea and Franklin, 2013). Data for all remaining basins are obtained from the US Navy’s Joint Typhoon Warning Centre (JTWC) best-track files (Chu et al., 2002). In this study, ‘tropical storms’ refer to all named systems which reached a 1 min maximum sustained wind speed of 34 kt (39 mph; 17.5 m s\(^{-1}\)) or higher. We exclude the contribution from subtropical storms.

To accompany the observations we also track tropical storms in ERA-Interim. Data are on a 1° × 1° grid at a 6-hourly temporal resolution covering the period 1992–2013. Monthly-mean surface temperature and wind shear data (for assessment of landfall) are also obtained from ERA-Interim for the same period at the same resolution.

Observed sea-surface temperature (SST) anomalies for the equatorial Pacific Niño3.4 region (120°–170°W, 5°S–5°N) are from the NOAA Climate Prediction Center (CPC).\(^{1}\)

For assessment of tropical storm landfall, the Natural Earth land vector shapefile at 1:50-million scale\(^{2}\) is used to provide high-resolution land boundaries. We use the Python packages Iris (Iris, 2014), Cartopy (Cartopy, 2014), Matplotlib (Hunter, 2007) and Shapely (Shapely, 2014) for analysis and visualisation of data throughout this study.

2.3. Tracking methodology and analysis

Tropical storm-like features are detected and tracked in GloSea4, GloSea5 and ERA-Interim using TRACK (Hodges, 1995, 1996, 1999; Bengtsson et al., 2007). This resolution-independent algorithm applies a standard detection criterion across all ocean basins and models, allowing a direct comparison between different resolution data to be made. Following the analysis of Roberts et al. (2014), tropical storms are identified as maxima in 850 hPa relative vorticity, spectrally filtered to T42 (∼250 km) resolution, and then a warm core check is applied at T63 (∼180 km) resolution over four vertical pressure levels (850, 500, 300 and 200 hPa). (This is in contrast to Strachan et al. (2013) and Bell et al. (2013) who used three vertical levels.)

All storms with a warm core and a lifetime of 2 days or more are retained for further analysis. Results are obtained for each hemisphere individually and we further subdivide storms by basin (Figure 1) based on their location of maximum intensity.

The ACE index of each storm is determined as follows: for observations, following the definition of Bell et al. (2000), the ACE index is the sum of the square of the maximum sustained 1 min surface wind speed every 6 h whilst the storm is at least tropical storm strength (winds ≥39 mph). In the models and reanalysis, for which wind speeds are too low to calculate ACE at the required threshold, we remove the wind speed threshold entirely and instead calculate ACE as the sum of the square of the maximum wind speed (at 925 hPa) every 6 h throughout the lifetime of the storm. Similar approaches for calculating model ACE index have also been used in other studies (e.g. Camargo et al., 2005; Shaevitz et al., 2014).

Track density plots are generated by binning storm tracks into 4° × 4° boxes and then normalizing by dividing by ensemble size and length of season (for comparison with Strachan et al., 2013; Roberts et al., 2014). To allow the tracking results to be as directly comparable to observations as possible, only the portions of the track which satisfy the warm-core criterion are assessed throughout this study.

3. Results

In this section we compare tropical storm characteristics in GloSea5 with those in GloSea4, ERA-Interim and observations over the period 1996–2009. Performance is assessed in terms of ability to reproduce observed geographical distribution, genesis locations, frequency, interannual variability, seasonality and dependence on ENSO. Results are presented for NH and SH basins covering the main tropical storm seasons June–November and November–April, respectively.

3.1. Geographical distribution and annual numbers

The spatial distribution of tropical storm tracks in GloSea4, GloSea5, ERA-Interim and observations are shown in Figure 2. Corresponding numbers of storms for each ocean basin are shown in Figure 3.

The spatial distribution of storm tracks is very similar between the two models, with GloSea5 showing the same locations of peak track density as GloSea4 but stronger in magnitude. Thus, in all ocean basins, the frequency of tropical storms is higher in GloSea5 than in GloSea4 (Figure 3). A similar distribution of storm track density using the same model, but at different resolutions, has also been shown in other studies (e.g. Strachan et al., 2013; Shaevitz et al., 2014; Roberts et al., 2014).

In the North Atlantic, tropical storm frequency is generally under-simulated by both GloSea4 and GloSea5, in agreement with previous studies (e.g. Bengtsson et al., 2007; Strachan et al., 2013; Camargo, 2013; Kim et al., 2014; Vecchi et al., 2014). However, there is an east/west split in storm tracks. In the eastern tropical Atlantic, the frequency of storms is improved in GloSea5 when compared to GloSea4, and is closer to the observed track density. This region is important for the formation of the most

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\(^{1}\)Available online at http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml (accessed 23 January 2015).

\(^{2}\)Available online at http://www.naturalearthdata.com/ (accessed 23 January 2015).

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Figure 1. Tropical storm tracking regions: North Atlantic (NA), Eastern Pacific (EP), Western Pacific (WP), North Indian Ocean (NI), Southwest Indian Ocean (SWI), Australian region (AU), South Pacific (SP) and South Atlantic (SA).
intense storms, so-called 'Cape Verde hurricanes', which account for more than 70% of tropical storm damage in the US (Landsea, 1993). In contrast, in the western Atlantic (Caribbean Sea, Gulf of Mexico and US East Coast), the density of tropical storm tracks is too low, both in the models and reanalysis. A lack of storms in the Caribbean region is also shown in other studies (e.g. Camargo et al., 2005; Strazzo et al., 2013; Mei et al., 2014; Vecchi et al., 2014), but it is not common to all models (e.g. Roberts et al., 2014). Failing to capture storms in the Caribbean region may have consequences for forecasts of landfall since many of these storms later impact the US Gulf coast (Lyons, 2004).

In the eastern Pacific, the location of maximum storm frequency off the Mexican coast is well captured by GloSea4 and GloSea5. However, in both models, the tracks seem to exhibit a stronger zonal component (i.e. retain a westward motion instead of recurving or dissipating) than in reanalysis and observations. As a result, too many storms are simulated in the central Pacific. A similar bias is also found using a fully coupled model of similar resolution to GloSea5 in Kim et al. (2014).

In the western Pacific, model storm tracks are also more zonal than observed, with many entering the basin from the central Pacific. Nevertheless the observed peak in activity over the South China Sea and to the east of the Philippines is well captured, particularly by GloSea5. GloSea5 also shows storms reaching higher latitudes compared to GloSea4, which is important for assessment of landfall in countries such as South Korea and Japan.

In the North Indian Ocean, both models show a peak in activity in the Bay of Bengal which is too strong and shifted too far north over the Indian subcontinent compared to observations and reanalysis. However, the magnitude of the anomaly has been reduced in GloSea5. Neither model is able to capture a small local peak in tropical storm activity in the Arabian Sea.

In the SH, GloSea5 simulates too many storms in the southwest Indian Ocean and the South Pacific, which is also seen in other studies (e.g. Strachan et al., 2013; Camargo, 2013; Roberts et al., 2014). However, observed peaks in tropical storm activity to the east of Madagascar and around Australia are well captured by the models. There are also very few simulated storms in the South Atlantic where observed storms are rare.

3.2. Genesis locations

In addition to examining the spatial distribution of storm tracks, it is also important to explore locations of tropical storm formation (or genesis). Figure 4 shows the mean location of tropical storm genesis by latitude and longitude for observations, ERA-Interim and the two models. Observed tropical storm genesis...
is concentrated within the narrow band 30°S–30°N, with two clearly defined peaks—one in the SH around 15°S and another, slightly larger peak in the NH around 10°N—and a minimum around the Equator. Both ERA-Interim and the models are in remarkably good agreement with observations, each exhibiting peaks in the correct locations and displaying the observed interhemispheric asymmetry. The peak in the SH is very closely matched in terms of magnitude by ERA-Interim and GloSea4, although both show a slight deficit in genesis in the NH. GloSea5, in contrast, has excessive genesis, particularly in the SH.

Closer examination of genesis frequency by basin (Figure 4(a)) reveals peaks in observed activity around 80°E (southwest Indian Ocean), 140°E (western Pacific) and 250°E (eastern Pacific), which are well captured by ERA-Interim and the models. The reanalysis and the models both underestimate genesis in the western tropical Atlantic (~290°E) and eastern Pacific (~250°E). GloSea5 also shows an additional bias in the Pacific Ocean with an excess of genesis from 160°E to 240°E (central and western North Pacific and southwest Pacific).

3.2.1. Eastern Atlantic

In the eastern tropical Atlantic (~40°W), tropical storm genesis is higher in GloSea5 than in GloSea4 and lies close to observations. In this part of the basin ~60% (Landsea, 1993) of observed tropical storms form from African Easterly Waves (AEWs) which travel westward from the west coast of Africa towards the Caribbean Sea (e.g. Burpee, 1974). These waves typically occur in the vicinity of the mid-tropospheric African easterly jet (AEJ), which is centred around 15°N during the NH summer (Hsieh and Cook, 2005). The mean monthly frequency and strength of AEWs in ERA-Interim and the models, as calculated using the method of Bain et al. (2013), is shown for May–October 1996–2009 in Figure 5(a,b), respectively. This method uses object-orientated image processing of Hovmöller diagrams of 700 hPa curvature vorticity to identify propagating easterly waves. The corresponding strength and location of the AEJ, identified as a maximum in August–September-averaged 700 hPa zonal wind around 15°W, is shown in Figure 5(c).

The mean frequency of AEWs, as well as the strength and location of the AEJ is very similar between the two models and lie reasonably close to ERA-Interim, particularly early in the season. Both models have a peak in AEW frequency around August, with the frequency somewhat underestimated compared to ERA-Interim during the peak months of August and September. The mean vorticity strength of AEWs is stronger in GloSea5 than in GloSea4, but still weaker both in magnitude and seasonal cycle amplitude than ERA-Interim. Nevertheless, the enhanced vorticity strength may provide stronger precursor systems from which tropical storms can develop, and may be one reason why the density of storm tracks in the eastern Atlantic is higher in GloSea5 than in GloSea4 (Figure 2). It is also interesting to note that an uncoupled version of HadGEM3 at the same resolution as GloSea5 has a poorer simulation of the AEJ structure and has significantly less tropical storm formation in the eastern Atlantic (Roberts et al., 2014). Initialisation of the land surface, in particular soil moisture (e.g. Yamada et al., 2012) and SSTs, both of which influence the position and magnitude of the AEJ (Cook, 1999), likely play a role in the improved tropical storm simulations in the eastern Atlantic in GloSea5. Work is ongoing to further understand the links between initialisation, land surface properties, jet structure and AEW formation.

3.3. Interannual variability

The interannual variability of tropical storm numbers and ACE index is firstly assessed for the period 1996–2009 to enable comparison between GloSea4 and GloSea5, and secondly for the longer period 1992–2013 for which supplementary data for GloSea5 are available.

3.3.1. Tropical storm frequency

The interannual variability of tropical storm numbers in the North Atlantic, western Pacific and Australian region are shown for GloSea4, GloSea5, ERA-Interim and observations for the period 1996–2009 in Figure 6. The standard deviation of the two models is also shown. Results are normalised for each year by subtracting the mean of the whole ensemble for all years and then dividing by the standard deviation of the ensemble means. Corresponding linear correlations between observed and
ensemble-mean numbers of storms are shown, for all ocean basins, basins in Table 1.

Statistically significant skill (95% level) is found for predictions of tropical storm numbers using GloSea5 in the North Atlantic (0.51), western Pacific (0.57), Australian region (0.69) and South Pacific (0.68). In the western Pacific and Australian regions the skill of GloSea5 is comparable to ERA-Interim. In the South Pacific (0.57), western Pacific (0.72), Indian Ocean (0.69) and South Pacific (0.69). These correlations, apart from predictions of ACE index in the eastern Pacific, remain significant when taking into account autocorrelation in the timeseries. Using the bootstrap resampling technique (as performed previously for tropical storm numbers), GloSea5 shows significant improvements in skill over GloSea4 for predictions of ACE index in the Australian region; for all other basins the difference in skill between the two systems is not statistically significant.

For the longer period 1992–2013 (Figure 7), GloSea5 retains significant skill for predictions of tropical storm frequency in the North Atlantic and western Pacific; statistically significant skill is also found in the eastern Pacific (Table 2).

The evidence of skill for numbers of tropical storms using GloSea5, particularly in the eastern and western Pacific, Australian region and South Pacific, is extremely encouraging and may enable operational forecasts of tropical storm frequency to be produced for these regions in the future.

3.3.2. ACE index

The variability of ACE index in GloSea4, GloSea5, ERA-Interim and observations is shown for the North Atlantic, western Pacific and Australian region for the period 1996–2009 in Figure 8. Corresponding linear correlations for all ocean basins are shown in Table 3.

GloSea5 shows statistically significant skill (95% level) for predictions of ACE index in all basins, apart from the North and southwest Indian Oceans: North Atlantic (0.56), eastern Pacific (0.62), western Pacific (0.81), Australian region (0.62) and South Pacific (0.67). In each of these basins the skill of GloSea5 is comparable to that of ERA-Interim. For comparison, GloSea4 shows significant skill in the eastern Pacific (0.61), western Pacific (0.78), southwest Indian Ocean (0.47) and South Pacific (0.69). These correlations, apart from predictions of ACE index in the southwest Indian Ocean (GloSea4), remain significant even when taking into account autocorrelation in the timeseries. Using the bootstrap resampling technique (as performed previously for tropical storm numbers), GloSea5 shows significant improvements in skill over GloSea4 for predictions of ACE index in the Australian region; for all other basins the difference in skill between the two systems is not significant.

Over the longer period 1992–2013, GloSea5 retains significant skill for predictions of ACE index in the North Atlantic, eastern Pacific and western Pacific (Table 2).

It is interesting to note that in both the models and reanalysis the skill of predictions of ACE index in the eastern and western Pacific is greater than that for tropical storm frequency. Similar results were also observed in low-resolution models (e.g. Camargo et al., 2005) and is potentially due to the stronger relationship between ACE index and ENSO in these basins (Camargo and Sobel, 2005).

3.4. Seasonal cycle

The seasonal cycle of tropical storm activity (calculated as the mean frequency of storm genesis per month) is shown for GloSea4, GloSea5, ERA-Interim and observations in Figure 9. The seasonal cycle is similar between reanalysis and the models, and lies close to observations, although basin-dependent biases are present.

In the North Atlantic, ERA-Interim and the models are able to capture observed tropical storm activity between June and November, with a peak in September. However, the frequency of storms is too low throughout the season, likely due to a lack of genesis in the western tropical Atlantic and Caribbean region (Figure 4) and too few AEWs during August and September (Figure 5). A similar bias is also present in other models (e.g. Camargo et al., 2005; Camargo, 2013; Shaevitz et al., 2014; Roberts et al., 2014).

In the eastern Pacific the seasonal cycle is very well simulated by ERA-Interim and the models, with both the amplitude and shape lying close to observations in all months apart from August.

In the western Pacific observed tropical storm activity occurs all year round, but peaks in the NH summer between May

Figure 5. Monthly mean numbers of (a) African easterly waves (AEWs) with positive curvature vorticity at 700 hPa from 5 to 15°N, 15°W; and (b) AEW mean 700 hPa curvature vorticity for ERA-Interim (black dotted line), GloSea5 (red) and GloSea4 (blue) from 1996 to 2009. The model ensemble spread is denoted by the coloured shading. (c) shows the August–September averaged 700 hPa zonal wind at 15°W indicating the location of the AEW around 15°N.
Figure 6. Normalised tropical storm counts for the North Atlantic (top), western Pacific (middle) and Australian region (bottom) in (a) GloSea4 and (b) GloSea5 over the period 1996–2009. Observations are shown as a black solid line; ERA-Interim as a black dotted line. Grey shading denotes ±1 standard deviation about the model mean (also normalised). Results are normalised for each year by subtracting the mean of the whole ensemble for all years and then dividing by the standard deviation of the ensemble means. North Atlantic and western Pacific results are for June–November; Australian region November–April.

Table 1. Pearson linear correlations (and p-values) of interannual variability of tropical storm frequency from the models and reanalysis with observations for individual ocean basins as defined in Figure 1 over the period 1996–2009.

|                  | North Atlantic | Eastern Pacific | Western Pacific | N Indian Ocean | SW Indian Ocean | Australian region | South Pacific |
|------------------|----------------|-----------------|-----------------|----------------|------------------|-------------------|---------------|
| GloSea4          | 0.24 (0.205)   | 0.27 (0.173)    | 0.39 (0.085)    | 0.09 (0.378)   | 0.36 (0.101)    | 0.25 (0.190)      | 0.72 (0.002)   |
| GloSea5          | 0.51 (0.030)   | 0.35 (0.112)    | 0.57 (0.016)    | 0.20 (0.251)   | 0.67 (0.401)    | 0.69 (0.003)      | 0.68 (0.003)   |
| ERA-Interim      | 0.70 (0.003)   | 0.37 (0.093)    | 0.60 (0.012)    | 0.37 (0.100)   | 0.82 (0.000)    | 0.63 (0.008)      | 0.76 (0.001)   |

Northern Hemisphere basins June–November; Southern Hemisphere basins November–April. GloSea4 and GloSea5 show the ensemble-mean correlation. Bold implies statistical significance at the 95% level.

and November. The shape of the seasonal cycle is reasonably well captured by GloSea5 which shows improvement over GloSea4, although activity is oversimulated from September onwards. A similar result using the High-Resolution Atmospheric Model (HiRAM) model is presented in Shaevitz et al. (2014).

In the North Indian Ocean the seasonal cycle is poorly simulated by both ERA-Interim and the models. The North Indian Ocean has two observed tropical storm seasons: in the NH spring and autumn, with corresponding peaks in activity in May and November. In the models, the first peak in tropical storm activity occurs in July and the second peak occurs in October. Tropical storms are also simulated in July and August when there are no recorded observations. The poor simulation of storms in this basin may be partly due to the incorrect detection of monsoon depressions by the tracking algorithm. However, both low- and high-resolution models are generally unable to properly simulate the seasonal cycle in this basin (e.g. Camargo et al., 2005; Shaevitz et al., 2014).

In the SH, the majority of observed tropical storm activity occurs between November and April, which is well captured by ERA-Interim and the models. However, in the models, peak season occurs one month earlier or one month later than observed and activity is generally overestimated in all basins, apart from the Australian region.

3.5. Influence of ENSO on storm track density

ENSO has a well documented impact on tropical storm activity globally (e.g. Camargo et al., 2010). Here we assess the impact of ENSO on storm track density in GloSea4, GloSea5, ERA-Interim and observations. El Niño (EN) and La Niña (LN) events are here defined as August–October averaged SST anomalies of ≥0.5 and ≤−0.5°C in the Niño3.4 region, respectively. Based on this criterion, five years are classified as EN: 1997, 2002, 2004, 2006 and 2009; and four years as LN: 1998, 1999, 2000 and 2007. Storm tracks during these years are then selected from observations, models and reanalysis (the actual ENSO state in the forecast systems is not considered). Significance tests are then used to judge the robustness of the response. It should be noted that, given the small sample size of the observations, we compare only the large-scale features to the model results. Results are compared to those documented in the literature where possible.

Figure 10 shows the difference in track density between EN and LN events over the period 1996–2009 for all ocean basins. The
models generally show a good response to ENSO, with changes in track density occurring in observed locations, consistent with the findings of previous studies (e.g. Shaevitz et al., 2014; Wang et al., 2014; Kim et al., 2014).

In the North Atlantic, the reduction in observed tropical storm activity in the tropical Atlantic and Caribbean region during EN events (Gray, 1984a) is well captured by the seasonal forecast systems, with GloSea5 showing a statistically significant (90% level) reduction in tropical storm frequency in these regions during EN years. A similar reduction in tropical storm frequency in the Atlantic during EN events is also shown in other studies (e.g. Wang et al., 2014;
Table 2. As Table 1 but for interannual variability of tropical storm frequency and ACE index in GloSea5 and ERA-Interim for the extended period 1992–2013.

| Data          | North Atlantic | Eastern Pacific | Western Pacific | North Indian Ocean |
|---------------|----------------|-----------------|-----------------|--------------------|
| Tropical storm frequency | GloSea5        | 0.59 (0.002)   | 0.60 (0.002)   | 0.65 (0.001)       | 0.03 (0.451)       |
|                | ERA-Interim    | 0.77 (0.000)   | 0.40 (0.032)   | 0.73 (0.000)       | 0.19 (0.200)       |
| ACE index     | GloSea5        | 0.52 (0.006)   | 0.75 (0.000)   | 0.80 (0.000)       | −0.14 (0.272)      |
|                | ERA-Interim    | 0.84 (0.000)   | 0.33 (0.066)   | 0.88 (0.000)       | 0.42 (0.027)       |

Table 3. As Table 1, but for the accumulated cyclone energy (ACE) index.

| Data          | North Atlantic | Eastern Pacific | Western Pacific | N Indian Ocean | SW Indian Ocean | Australian region | South Pacific |
|---------------|----------------|-----------------|-----------------|----------------|-----------------|-------------------|---------------|
| GloSea4       | 0.32 (0.133)   | 0.61 (0.011)    | 0.78 (0.000)    | −0.05 (0.439)  | 0.47 (0.046)    | 0.12 (0.338)      | 0.69 (0.005)  |
| GloSea5       | 0.56 (0.019)   | 0.62 (0.009)    | 0.81 (0.000)    | −0.31 (0.141)  | 0.29 (0.244)    | 0.62 (0.009)      | 0.67 (0.005)  |
| ERA-Interim   | 0.88 (0.000)   | 0.65 (0.006)    | 0.91 (0.000)    | 0.53 (0.024)   | 0.79 (0.000)    | 0.78 (0.000)      | 0.56 (0.018)  |

Another well-documented impact of ENSO in the western Pacific is on the location of tropical storm genesis, with storms more likely to form to the southeast of the basin, closer to the dateline, during EN events and to the northwest of the basin during LN events (e.g. Chan, 1985; Chia and Ropelewski, 2002). The mean genesis location of storms in the western Pacific during EN and LN events are shown for observations, ERA-Interim, GloSea4 and GloSea5 in Figure 11. Both the models and ERA-Interim are able to simulate a shift in genesis location with ENSO, although the strength and location is better captured by GloSea4 than GloSea5. Capturing changes in genesis location is not only important for forecasts of tropical storm intensity and ACE index (Camargo and Sobel, 2005) but also for landfall studies, due to changes in storm tracks (e.g. Wang and Chan, 2002; Camargo...
Figure 10. Monthly mean storm track density difference between El Niño and La Niña events for (a) GloSea4, (b) GloSea5, (c) ERA-Interim and (d) observations. El Niño years are 1997, 2002, 2004, 2006 and 2009; La Niña years are 1998, 1999, 2000 and 2007. Red (blue) anomalies show enhanced (reduced) activity during El Niño events. Northern Hemisphere season June–November; Southern Hemisphere season November–April. Stippling shows where changes have a p-value < 0.1 using a two-tailed Student’s t-test. Model results are normalised with respect to ensemble size for comparison with the observed transits.

Figure 11. Seasonal mean location of tropical storm genesis in the western Pacific during El Niño (squares) and La Niña (triangles) events for GloSea4 (blue), GloSea5 (red), ERA-Interim (black dotted line) and observations (black solid line). El Niño years are 1997, 2002, 2004, 2006 and 2009; La Niña years are 1998, 1999, 2000 and 2007.

et al., 2007b): landfall in Korea and Japan is enhanced during EN years (Fudeyasu et al., 2006; Goh and Chan, 2012), whereas storms are more likely to impact countries surrounding the South China Sea during LN years (e.g. Wu et al., 2004; Goh and Chan, 2010; Zhang et al., 2012).

In the North Indian Ocean, the observed decrease in tropical storm frequency in the Bay of Bengal during EN events (e.g. Felton et al., 2013) is not well represented by either ERA-Interim or the models. However, the incorrect (positive) anomaly shown in GloSea4 and ERA-Interim is reduced in GloSea5.

In the South Pacific, tropical storms tend to occur further north, closer to the Equator, and increase in frequency in the central and southwest regions during EN years (Camargo et al., 2007a; Chand et al., 2012). Tropical storm activity is also reduced around western Australia (Camargo et al., 2007a). These patterns are well represented by the models and are statistically significant (90% level) in GloSea5.

3.6. Landfall

In this section we focus on the ability of GloSea5 to predict landfall frequency in the North Atlantic basin. Two regions are assessed: the US coast (including Nova Scotia) and the Caribbean (comprising the coasts of Mexico, Central America and the Caribbean). A graphical representation of these regions is shown in Figure 12. Skill is firstly assessed by directly counting the frequency of tropical storm landfalls in GloSea5 and comparing these to observations. A second assessment then compares the skill between observed landfall counts and model-based indices, such as Atlantic basin-wide storm counts, to examine whether these can more skilfully predict risk of tropical storm landfall.

3.6.1. Counting method

In this first assessment we use a simple definition of landfall: a landfall event occurs when the track of a tropical storm crosses a land boundary. Each storm can only contribute towards the landfall count in each region once, even if more than one landfall occurred. For example, Hurricane Katrina (Figure 12) made multiple landfalls along the US coast and one landfall in the Caribbean. Based on our simple counting method, Katrina would contribute a landfall count of 1 for the USA and 1 for the Caribbean. Landfalls throughout the whole lifetime of the storm are considered, therefore all landfall intensities from tropical depression to major hurricane strength are included. The track of the storm is created from the 6 hourly storm locations provided by the model or observations; we do not interpolate the tracks to finer temporal resolution such as in Kossin et al. (2010). Thus the exact locations of landfall in observations may differ slightly from those used here if an observation point at landfall is not recorded. Bypassing storms (i.e. those that moved close to or parallel to the coastline, but did not cross it) are excluded. The same counting method...
is applied to all storms in observations, ERA-Interim and GloSea5.

To test the method is robust, we apply it to the observed North Atlantic tropical storm database HURDAT2 to create landfall counts for the US coast (hereafter referred to as HURDAT landfalls) and compare these with the official US tropical storm and hurricane landfalls documented by the National Hurricane Center9 (not shown). The correlation between the two datasets is 0.95 over the 1992–2013 period, showing the method provides a good approximation of landfall frequency along the US coast.

The interannual variability of tropical storm landfall frequency along the US coast and the Caribbean is shown for GloSea5, ERA-Interim and observations over the period 1992–2013 in Figure 13. Corresponding correlations are shown in Table 4. In the Caribbean, GloSea5 predicts the observed interannual variability in landfall frequency, with significant correlations (95% level) between the model ensemble mean and observed landfall count (0.69). Statistically significant skill is also found for this region in ERA-Interim (0.66). GloSea5 is able to predict the observed increase in landfall frequency in 1995 and 1996 as well as reduced landfall frequency in 1992 and 1998. The most active season, 2005, which observed a record 15 landfalling tropical storms across the basin (Bell et al., 2006), has the correct sign of the response, but is underestimated in magnitude. GloSea5 shows the highest landfall frequency during the 22 year period in 2010, which was not observed. Similar difficulty in predicting landfalls using climate models during this season have also been highlighted by Vecchi and Villarini (2014).

Along the US coast, we find low skill (r = 0.22) for predictions of tropical storm landfall using GloSea5 for the period 1992–2013, despite significant skill for this region in ERA-Interim (0.68). Our results are therefore consistent with the findings of Vecchi et al. (2014) who also found some predictive skill for tropical storm landfall in the Caribbean, yet limited skill along the US coast. In GloSea5, the low skill may in part be due to the density of storm tracks around the US coast, which is much lower than observed (Figure 2). This bias likely comes from two separate sources: firstly due to a lack of genesis in the Caribbean Sea and Gulf of Mexico, which may impact estimates of landfall along the US Gulf Coast (Lyons, 2004), and secondly from storms with genesis in the eastern Atlantic which do not have a long enough storm track to reach the US coast. Reasons for the low track density and landfall skill around the US coast in GloSea5 is currently being investigated.

3.6.2. Relationship with other indices

Tropical storm landfall can be influenced by changes in the large-scale environment, for example, a result of ENSO, which may be predictable on seasonal timescales. ENSO influences tropical storm activity in the North Atlantic primarily through changes in vertical wind shear over the Caribbean Sea and the Atlantic hurricane main development region (MDR; 10–20°N, 20–60°W) (Gray, 1984a; Camargo et al., 2007a), which then influence the location of tropical storm genesis, tracks and landfall (e.g. Wang et al., 2014). Recent studies (e.g. Camargo, 2013) have shown that climate models may simulate changes in the large-scale environment better than tropical storms directly, potentially offering an alternative method for predicting risk of landfall. Here we assess the influence of both local and remote conditions which have well-documented influences on tropical storm landfall in the North Atlantic.

The relationships between observed HURDAT landfalls (as calculated using the counting method described above) and predicted Atlantic basin-wide storm counts (June–November), Pacific Ni˜no3.4 SSTS (August–October), Atlantic MDR SSTS (August–October) and Atlantic MDR vertical wind shear (August–October) are presented for GloSea5 and ERA-Interim for the US coast and Caribbean for the period 1992–2013 in Table 5.

For the US coast in ERA-Interim, the Atlantic basin-wide storm count and Atlantic MDR wind shear show a significant correlation with HURDAT landfalls (0.49 and −0.38, respectively), while Ni˜no3.4 SSTS and Atlantic MDR SSTS show no significant correlations. In GloSea5 we find no correlation between observed landfalls with any of the assessed indices, including Atlantic basin-wide storm counts. For ERA-Interim, the method of counting US landfalls directly from landfalling storm tracks provides statistically significant skill, which is larger than the correlation with the individual predictors. For GloSea5, no skill is found for predictions of US landfall using either the landfall method or the individual predictors.

For the Caribbean region, all indices apart from Atlantic MDR SSTS in ERA-Interim show significant correlations with observed HURDAT landfalls. The correlation with basin-wide storm counts (0.64 GloSea5; 0.77 ERA-Interim) is comparable to the skill of directly counting landfalls (0.69 and 0.66, respectively). However, if we account for autocorrelation in the timeseries then only Atlantic basin-wide storm counts and Atlantic MDR SSTS (GloSea5 only) retain a significant correlation with observed landfalls, with basin-wide storm counts generally showing greater skill than MDR SSTS.

To summarise, GloSea5 shows skill for predictions of tropical storm landfall in the Caribbean over the period 1992–2013. Skill is similar using either the direct counting of landfalling storms in the model or by inferring landfall frequency from the Atlantic basin-wide storm count. Along the US coast we find no statistically significant skill for predictions of landfall using either the landfall method or any of the assessed indices, including basin-wide storm counts. Recent studies have shown that the

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9US landfalling tropical storms http://www.aoml.noaa.gov/hrd/hurdat/ustorms.html and hurricanes http://www.aoml.noaa.gov/hrd/hurdat/All_U.S_Hurricanes.html (accessed 23 January 2015).

Table 4. Pearson linear correlations (and p-values) between observed and GloSea5 ensemble-mean and ERA-Interim predicted landfall frequency along the US coast and the Caribbean for the period June–November 1992–2013.

| Region       | US coast | Caribbean |
|--------------|----------|-----------|
| GloSea5      | 0.22 (0.164) | 0.69 (0.000) |
| ERA-Interim  | 0.68 (0.000)  | 0.66 (0.000)  |

Bold implies significance at the 95% level.
tracks of model tropical storms (and therefore landfall rates) are sensitive to the model’s dynamical core (Reed and Jablonowski, 2012), convective scheme (e.g. Reed and Jablonowski, 2011; Zhao et al., 2012) and its representation of the mean climate (e.g. Vecchi et al., 2014; Kim et al., 2014); thus improvements to any of these components may allow regional predictions of US landfall risk in the future.

4. Conclusions

The variability of tropical storm activity is assessed in the Met Office Global Seasonal Forecast System version 5 (GloSea5) and compared to the predecessor system GloSea4, ERA-Interim reanalysis and observations over the common period of the operational hindcast for both systems: June–November and November–April 1996–2009. Both systems are assessed for their ability to reproduce the observed tropical storm climatology (e.g. storm tracks, frequency and seasonal cycle) as well as interannual variability and changes in storm track density with ENSO. A supplementary assessment of GloSea5 for the period 1992–2013 was also performed to evaluate skill of predictions of tropical storm activity in NH basins as well as landfall risk along the US coast and the Caribbean over a longer period. The period was extended to allow assessment of landfall in more recent years, such as 2010, which recorded above-normal tropical storm activity but no US landfalling hurricanes.

Tropical storms are detected and tracked in GloSea4, GloSea5 and ERA-Interim using the same methodology (TRACK; Hodges, 1995). The main conclusions of this study are:

- GloSea5 shows statistically significant skill for predictions of tropical storm frequency and ACE index in nearly all ocean basins. The greatest skill is found in the North Atlantic, western Pacific, Australian region and South Pacific, with GloSea5 showing significantly improved skill over GloSea4 in the North Atlantic and Australian region.
- GloSea5 is able to reproduce key tropical storm characteristics, such as the observed geographical distribution, seasonal cycle, and spatial changes in storm track density with the phase of ENSO.
- Statistically significant skill is found for predictions of tropical storm landfall frequency in the Caribbean (section 3.6 gives definitions) using GloSea5 over the period 1992–2013. Skill is similar using either the direct counting system, which is due to become operational in February 2015. This system will have the same resolution as GloSea5, but a different dynamical core (Wood et al., 2014), which is hoped to further improve predictability of seasonal tropical storm variability and landfall around the world.

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