On the seasonal and sub-seasonal factors influencing East China tropical cyclone landfall

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Abstract
To date it has proved difficult to make seasonal forecasts of tropical cyclones, particularly for landfall and in East China specifically. This study examines sources of predictability for the number of landfalling typhoons in East China on seasonal (June–October) and sub-seasonal time scales. East China landfall count is shown to be independent of basin-scale properties of TC tracks, such the genesis location, duration, basin track direction and length, and basin total count. Large-scale environmental climate indices which are potential basin scale drivers are also shown to be largely uncorrelated with landfall prior to and throughout the season. The most important factor is the steering in the final stages to landfall. The seasonal landfall is strongly anti-correlated with the more local zonal mid-tropospheric wind field over the East China sea ($r = -0.61$, $p < .001$). It is proposed that geopotential height anomalies over Korea/Japan cause anomalous easterly winds in the East China Sea and enhance landfall rates by steering typhoons onto the coast. Early, peak, and late sub-seasonal landfall counts are shown to be independent of each other yet share this predictor. This local feature may be dynamically predictable allowing a potential hybrid dynamical-statistical seasonal forecast of landfall.

KEYWORDS
East China, landfall, tropical cyclone

1 | INTRODUCTION

There is great need for the prediction of the seasonal activity of landfalling TCs for businesses, governmental organisations and the general public. Attempts to predict TC seasonal activity date back to the work of Nicholls (1979) and Gray (1984). Skillful predictions are for basin-averaged TC indices rather than landfall (Vitart and Stockdale, 2001; LaRow et al., 2010; Smith et al., 2010; Villarini et al., 2010). It has been shown that basin-aggregated metrics do not represent landfall well (Pielke, 2009) and conceal significant regional variability in activity (Vecchi et al., 2014). This led to studies of the factors directly governing landfall frequency (Liu and Chan, 2003; Zhang et al., 2013). The Western North Pacific (WNP) is the most active ocean basin with the highest human exposure and economic growth (Peduzzi et al., 2012). Kossin et al. (2014, 2016) have shown a poleward shift of TCs peak intensity which may be linked to climate change. This northward shift makes seasonal predictions of landfalling typhoon activity in East China more urgent.
Chan and Xu (2009) note that seasonal East China landfall counts are uncorrelated with the other regional counts. Huang and Chan (2014) show that East China TC activity is the worst represented region in global hindcast data as well as having the lowest skill in dynamical downscaling forecasts. Yu et al. (2017) find that TC frequency in South East China is linked with position of the East Asian westerly jet, while (Gao et al., 2018, 2020) found connections between tropical North Atlantic sea surface temperature (SST) and landfall activity in China.

There is also sub-seasonal variability in the number of tropical cyclones making landfall in the WNP. Tian and Fan (2019) show that June–August (JJA) and September–November (SON) landfall counts for China are uncorrelated. Liu and Chan (2003) show that early and late season South China landfall activity have different relationships with ENSO. Goh and Chan (2010) fit separate sub-seasonal models for South China landfall. The western Pacific subtropical high (WPSH) has been identified as an important driver of TC activity (Wang et al., 2013). Camp et al. (2019) show that a WPSH index is correlated with East China landfall but only in JJA. However, the East China TC season runs from June to October, and JJA typically accounts for only two thirds of landfalls. There is therefore a significant knowledge gap in the ability to forecast landfall for the entire season in East China. Such a climate service is likely to become increasingly important if the observed northward shift of TCs continues under climate change.

In this study, we examine the sources of predictability of East China TC landfall on the seasonal and sub-seasonal scale. East China landfall count is surprisingly shown to be independent of both many widely used environmental driving climate indices and basin-scale TC properties. We show that a significant fraction of seasonal and sub-seasonal East China landfall variability is instead explained using a simple East China Sea zonal wind index at the TC steering level.

## 2 DATA AND METHODS

Typhoon landfall data were derived from the Chinese Meteorological Administration (CMA) best track data set (Ying et al., 2014) which was extracted from the International Best Track Archive for Climate Stewardship (IBTrACS, v04r00) World Meteorological Organisation data (Knapp et al., 2010, 2018). The period considered was limited to the years 1979–2017 to coincide with the available reanalysis data. We consider all tracks in the database regardless of their intensity at landfall and refer to the systems as typhoons, tropical cyclones and storms interchangeably. A China landfall event was determined to have occurred at the first best track entry after the cyclone centre crosses the mainland coast in the latitude range 18°–40°N and longitude range 109°–124°E. China landfall events were then split into South China and East China categories according to the latitude at which they occur.

Basin aggregate properties of TC activity were calculated as seasonal (June–October) or sub-seasonal (June–July, August, September–October) means of all TCs in the data set. 90% of East China landfalls occur below 30°N hence we considered only TC activity below this latitude as a potential landfall factor and TC tracks were cropped to this region. From these tracks, seasonal or sub-seasonal mean TC genesis (Lon0, Lat0) and final location, duration (r) and maximum intensity (LMI) were calculated. The seasonal and sub-seasonal mean track direction (θ, anti-clockwise from east) and length (r) were then calculated from the mean genesis and final locations.

The geopotential height and wind speed reanalysis data come from European Centre for Medium-range Weather Forecasts (ECMWF) reanalysis ERA5 (Copernicus Climate Change Service, 2017). Monthly mean fields downscaled to 1° by 1° resolution were used in this analysis. The monthly mean sea surface temperature was from the Hadley Centre Sea Ice and Sea Surface Temperature data set (HadISST) (Rayner et al., 2003) on a 1° by 1° grid.

We use several existing environmental climate indices known to be drivers of WNP TC activity for correlation analysis. These include the Pacific Meridional Mode (PMM) and the Atlantic Meridional Mode (AMM) (Chiang and Vimont, 2004), the North Atlantic SST index (NASST) (Huo et al., 2015; Gao et al., 2018), the SST Gradient Index (SSTG) (Zhan et al., 2013), El Niño Modoki (Ashok et al., 2007), the Pacific Decadal Oscillation index (PDO) (Mantua et al., 1997), the Western Pacific Subtropical High Index (WPSH) (Wang et al., 2013), and the East Indian Ocean SST anomaly index (EIO) (Du et al., 2011). For a description of these indices see, for example, Zhang et al. (2017).

Poisson regression is typically used for modelling count data such as the annual total of East China landfalling typhoons (Villarini et al., 2010; Tippett et al., 2011). The model is validated using leave-one-out cross validation (Fan and Wang, 2009; Li et al., 2013) whereby model fitting and validation are performed separately for every year in the data. For each year, data are split into two sets: the training set (all years except the target year), and the validation set (the target year). Model fitting is performed using only the training set and validation only on the validation set. This removes the bias which would otherwise be present due to validating
the model on data which has used also been using in the fitting process and therefore improves assessment of out of sample model error.

3 | RESULTS

3.1 | Landfall count analysis

We first examine how to partition China landfall events into South and East groups. Figure S1 shows how the annual number of landfalling typhoons in South and East China and the Pearson’s correlation coefficient between them varies as a function of the latitude used to divide the two sets. The correlation between East and South China landfall reaches a broad minimum when the divide is between 23.5° and 24.5°N. We choose 23.5° as the divide as this most equally partitions East and South China landfall counts. Using this definition East and South China landfall counts are anti-correlated with a correlation coefficient of $-0.32$ which is significant at the 95% confidence level. This suggests that the two regions exhibit landfall count behaviour which needs to be modelled separately. The annual mean landfall counts for East and South China using this partition latitude are 2.7 and 3.3 respectively meaning the events are distributed approximately evenly across the two. This definition of East China landfall closely agrees with that of “Middle” Asian landfalling WNP TCs used by Chan and Xu (2009), East China Landfalls by Chan et al. (2012) and “Central” TCs by Camp et al. (2019). We use this partition latitude for the rest of this study and landfall counts refer to East China as defined above unless otherwise specified.

Figure 1a shows the genesis locations, tracks, and landfall locations of all tropical cyclones in the record satisfying our conditions for making landfall in East China. The map shows that most tracks travel northwestward from the WNP before making landfall in East China. Only a small portion (<10%) have origins in the South China Sea before making a northeast passage to landfall. Figure 1b shows how landfall events are distributed symmetrically around August across the landfall season. We divide the season up into three sub-seasonal periods, each with similar landfall. The June and July period (32 counts) is denoted “Early”, August (45) is “Peak”, September and October (26) constitute the “Late” season. We use the term “Season” to refer to the period June to October. Figure 1c is a histogram of season landfall with a peak at 3 landfalls per season (mean = 2.7). Also shown is a Poisson distribution of the same mean which is a standard distribution for count data. A chi-squared goodness of fit test finds the observed distribution of season landfall counts is not significantly different from a Poisson distribution.

The Early, Peak and Late sub-seasonal landfall counts are not significantly correlated with each other ($|r| < .14$, $p > .40$). This means that the three identified sub-seasonal periods have independent landfall activity and may therefore benefit from separate treatment when considering seasonal forecasting. It also suggests that the factors influencing East China landfall display variability on the sub-seasonal scale and are not persistent across the season. This finding of independence between East China landfall sub-seasons is broadly consistent with Tian and Fan (2019) observing that the JJA and SON sub-seasons for all China landfall counts appeared uncorrelated.

3.2 | Basin-scale landfall factors

We identify several TC properties which could be hypothesised to contribute to landfall probability. Basin aggregates of these TC properties across a TC season (or sub-season) may then be expected to affect the landfall probability for that season. This probability combined with the basin storm count governs the landfall count. We therefore calculate season (and sub-season) means of
the genesis location (Lon₀, Lat₀), TC duration (r), lifetime maximum intensity (LMI), track direction (θ), track length (τ) and storm count (NT). We can then use correlation analysis to determine the influence of these seasonal (sub-seasonal) basin properties on East China landfall counts. Correlations with East China landfall count are shown in Table 1. Surprisingly, we find the seasonal East China landfall count is not significantly correlated with the basin storm count (r = .24, p = .15). Further, we find that none of the other indices are significantly correlated (at the 95% confidence level) with landfall count on the seasonal scale. Sub-seasonal analysis shows that only the mean genesis latitude is significantly correlated (r = .37, p = .02), and only during the late season. It may seem surprising that basin storm count or genesis count is not significantly correlated with East China landfall. The “conversion rate” of a genesis/basin storm count into an East China landfall is only 11% but the interannual standard deviation of storm count is 5.2. Therefore storm count variability alone can only produce a standard deviation in landfall count of about 0.6 (0.11 × 5.2). Given that the observed standard deviation of landfall count (1.5) is 2.5 times greater we conclude that factors other than storm count must be more dominant contributors to the variability in East China landfall count and that these factors must affect the “conversion rate.”

The lack of correlation between potential basin-scale landfall factors and East China landfall indicates that climate indices which have been linked to driving basin wide TC behaviour—shifts in genesis location, changes to basin tracks, and modulations of basin-wide storm counts—are unlikely to significantly affect East China landfall counts. We verify this by examining an extensive set of known large-scale TC driving environmental climate indices, calculated quarterly (Table 2). None of the driving indices we examined are significantly correlated with East China landfall prior to the season (meaning they would not make useful predictors by themselves without a dynamical model) and only the AMM is significantly correlated (r = .35, p = .03) during the TC season.

Many of the driving climate indices are, as expected, strongly correlated with the TC basin properties described above reflecting their known utility for other WNP TC activity applications particularly at the basin scale (Table S1). The mean track direction is significantly correlated with the Niño Modoki index which has been shown to influence WNP steering (Zhang et al., 2012). Many of the driving climate indices are significantly correlated with the basin storm count including PMM (Zhang et al., 2016a) and EIO (Zhan et al., 2011). The Niño 3 and 3.4 indices are shown to be linked to a south east shift in genesis (Chia and Ropelewski, 2002). So while these existing climate indices have been shown to drive basin-scale TC properties which may be helpful in the prediction landfall in other regions, they do not help explain the variability of East China landfall.

While the above driving climate indices are all based on SST, we also examine the potential connection of SST with East China Landfall directly through correlation analysis (Figure S2). We find no large regions in tropics where SST is significantly correlated with East China landfall. This is consistent with the idea that TC genesis is not a strong factor contributing to East China Landfall. We do however find larger regions of significant positive correlation around the Sea of Japan and in the central north Pacific. These are likely linked to changes in environmental conditions examined below.

### 3.3 Steering over East China Sea

The above analysis suggests basin-scale analyses may be insufficient to determine influences on East China landfall and more local factors may be important. Figure 2a displays the correlation coefficient of seasonal landfall with seasonal mean geopotential height at 850 hPa, H850. The correlation in the WPSH region is only weakly

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**Table 1** Correlation of seasonal and sub-seasonal number of landfalling TCs in East China with basin aggregate TC properties derived from best track data

| Months    | ECU500   | KJH500   | NT   | Lat₀  | Lon₀  | r    | θ    | r     | LMI |
|-----------|----------|----------|------|-------|-------|------|------|-------|-----|
| Jun-Oct   | −0.61*** | 0.52***  | 0.24 | 0.3   | 0.04  | −0.02| 0.02 | 0     | 0.16|
| Jun-Jul   | −0.43**  | 0.15     | 0.15 | 0.19  | −0.16 | 0.06 | −0.02| −0.05 | −0.04|
| Aug       | −0.48**  | 0.41*    | 0.21 | 0.01  | 0.07  | 0.17 | 0.12 | 0.13  | 0.2 |
| Sep-Oct   | −0.45*** | 0.47***  | −0.02| 0.37* | 0.09  | −0.01| 0.09 | 0.1   | 0.24|

*Note: NT is the basin TC count, Lat₀ and Lon₀ are the genesis location, and r, θ and r are the basin track duration, direction and length, respectively. LMI is the TC lifetime maximum intensity. KJH500 is the geopotential height at 500 hPa over Korea and Japan and ECU500 is the zonal wind at 500 hPa over East China as defined in the text. Asterisks denote significance of correlation at 95% (*), 99% (**), and 99.9% (***).
anti-correlated with season landfall activity ($r = -0.24$, $p = 0.15$) as observed by Camp et al. (2019). This region also appears to be part of a much larger signal covering much of the tropics from beyond India to the Eastern Pacific. Low H850 in this region enhances cyclonic vorticity which acts in favour of increased storm counts. Critically, this vorticity in the WPSH region also leads to

**TABLE 2**

Correlation of quarterly climate indices and seasonal number of landfalling TCs in East China

| Months | ECU500 | KJH500 | WPSH | PMM | NiñoMod | NASST | Niño34 | Niño3 | SSTG | PDO | PMM | Niño34 | NASST | Niño34 | Niño3 | SSTG | PDO | PMM | Niño34 | NASST | Niño34 | Niño3 | SSTG | PDO | PMM | Niño34 | NASST |
|--------|--------|--------|------|-----|--------|-------|--------|-------|------|-----|-----|--------|-------|--------|-------|------|-----|------|-----|------|-------|--------|-------|------|-------|-----|------|-------|--------|
| OND    | -0.22  | 0.08   | -0.19| -0.06| 0.06   | -0.26 | -0.57***| -0.49**| 0.35*| -0.17| 0.24| 0.23  | -0.23 | 0.10  | -0.06 | -0.16| -0.16| -0.11| -0.11| -0.06| -0.14| -0.09| -0.09| -0.09| -0.09| -0.09| -0.09|
| JFM    | -0.06  | 0.09   | 0.02 | 0.02 | 0.03  | 0.03  | 0.03   | 0.03  | 0.05 | -0.05| 0.23| 0.03  | 0.03  | 0.03   | 0.03 | 0.03 | 0.05 | 0.23 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03|
| AMM    | 0.08   | 0.01   | -0.19| 0.09 | 0.02  | -0.06 | 0.06   | 0.06 | 0.08 | 0.08 | 0.35*| 0.35* | 0.35*  | 0.35* | 0.35* | 0.35*| 0.35*| 0.35*| 0.35*| 0.35*| 0.35*| 0.35*| 0.35*| 0.35*| 0.35*| 0.35*|
| JAS    | 0.04   | 0.01   | 0.04 | 0.04 | 0.04  | 0.04  | 0.04   | 0.04 | 0.04 | 0.04 | 0.04  | 0.04  | 0.04   | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04|

Note: Asterisks denote significance of correlation at 95% (*), 99% (**) and 99.9% (***). confidence levels.

**FIGURE 2** Maps of point-wise correlation coefficient of seasonal (June – October) number of landfalling TCs in East China with ERA5 reanalysis geopotential height at (a) 850 hPa and (b) 500 hPa, zonal (c) and meridional (d) wind speed at 500 hPa. White contours show regions of 99% significance. Black squares are boxes chosen to create KJH500 and ECU500 indices described in the text.
easterly flow anomalies in the East China area increasing the likelihood of TCs making landfall. A much stronger positive correlation in the H850 is seen centred on Korea and Japan. This is a feature quite separate from the WPSH. Positive anomalies of H850 are associated with anti-cyclonic flows which contribute to easterly flow anomalies over the East China Sea. Mid-tropospheric conditions are typically used to explore TC steering. Figure 2b shows the above analysis for geopotential height at 500 hPa. Here there is also a dipolar signal between the WPSH region and a larger area of high positive correlation over Japan and Korea. We note that this phenomenon is also likely linked to significant positive landfall correlation with SSTs in the Sea of Japan (Figure S2). A plausible cause of SST increases is that anticyclones (high geopotential height anomalies) also have low surface wind speeds (less evaporative cooling) and reduced cloud cover giving increased insolation.

Figure 2c shows that zonal wind at 500 hPa, U500, is strongly negatively correlated with landfall in a band centred at approximately 30°N stretching from the Chinese coast to the Central Pacific. This seasonal scale anomalous easterly associated with high landfall is a geostrophic response to the H500 dipole anomaly discussed above. This anomaly acts to direct WNP TC tracks onto the East China coast.

The correlation of meridional wind at 500 hPa (V500) and landfall is shown in Figure 2d. The patterns in the WNP TC track region is less clear in the meridional wind analysis. However, the negative (southerly) anomaly on the South China coast combined with the U500 westerly anomaly in the South China Sea and northern Philippines may help divert tracks headed for South China towards East China.

We now perform correlation analysis for our three identified sub-seasons (Figure S2). We find that generally the patterns described above for the seasonal correlation maps persist throughout the season from Early (Jun, Jul) through Peak (Aug) to Late (Sept, Oct) season. The positive correlation of landfall with H500 around Japan/Korea is present in all sub-seasons. Significant negative correlation of U500 with landfall associated with the easterly anomaly over the East China Sea is also present in all sub-seasons. The correlation patterns are strongest in the Peak sub-season. The meridional wind, V500, shows a persistent positive correlation with landfall in each sub-season. Although we have shown that Early, Peak and Late sub-seasonal counts are independent of each other, the sub-seasonal correlation analysis shows that robust and similar localised steering wind patterns over the East China Sea are associated with each sub-season count.

A box centred on the positive H500 correlation over Korea and Japan (125–145°E, 36–43°N) was chosen to create a H500 index (KJH500) which is strongly correlated with landfall \( (r = .52, p < .001) \) across the season. Similarly, a box over the negative U500 anomaly over the East China Sea (118–130°E, 26–33°N) was chosen to create a U500 index (ECU500) which is strongly anti-correlated with landfall \( (r = -.61, p < .001) \) across the season. The correlations of the KJH500 and ECU500 index for the season and each sub-season are shown in Table 1. Neither KJH500 nor ECU500 in the months prior to the TC season are correlated with East China landfall (Table 2).

The ECU500 index provides a measure of the anomalous zonal wind at the steering level around the East China Sea. Negative values correspond to easterly zonal wind anomalies which act to direct TCs passing through the East China Sea onto the coast. This direct physical mechanism leads to the strong negative correlation between the ECU500 index and East China landfall frequency. The easterly anomalies associated with high East China landfall frequency are a geostrophic response to high anomalies of midlevel geopotential height around Japan and Korea. The KJH500 index is a measure of this anomaly and while its interaction with TC tracks is one step less direct than the ECU500 index and has slightly weaker correlation with East China landfall, it may be more predictable and hence useful in forecasting landfall. Further to this, the geopotential height index appears to be closely related to the Bonin high, a summer anticyclone around Japan linked to the propagation of stationary Rossby waves along “the Silk Road pattern” (Enomoto et al., 2003).

### 3.4 Model prediction and validation

The predictability of the geopotential height in the Korea/Japan region by numerical models has been shown to be significantly skilful at the 95% confidence level by Zhang et al. (2016b). It may therefore be possible to build a sub-seasonal and seasonal forecast climate service by combining numerical models that predict the zonal wind on the East China coast or geopotential height over Korea/Japan and combine it with our found statistical relationship. To demonstrate the performance of this statistical relationship we use Poisson regression via a generalised linear model with seasonal (sub-seasonal) ECU500 as the predictor. Leave-one-out cross-validation was performed. Model validation statistics for the seasonal and sub-seasonal cases are shown in Table S2. Time series of observed and cross-validated predicted seasonal landfall are highly correlated \( (r = .59) \), shown in Figure S4. The cross-validated skill score for the seasonal forecast is 0.19 which outperforms Huang
and Chan (2014) who report a seasonal forecast skill of 0.06 for East China landfall using a dynamical downscaling methodology. We have not tried to optimise the performance of the predictive model through careful predictor region selection. Rather, we have shown that ECU500, which has a direct physical linkage to East China landfall, is also a skilful predictor.

### 4 | CONCLUSIONS

We showed that the seasonal numbers of typhoons that make landfall over East China and South China are anticorrelated (significant at the 95% level) and chose a definition which, while consistent with previous studies of regional TC activity, maximised the anti-correlation between the two. The East China landfall season was divided into early, peak and late sub-seasons and it was shown that landfall counts for these sub-seasons are independent of each other and therefore sub-seasonal scale analysis is necessary to make sub-seasonal predictions. The separation between intrinsic TC basin properties and external drivers gives some useful insights into explaining why the external drivers struggle to predict landfall although they do capture basin TC properties. Through correlation analysis we showed that several key basin-scale TC properties (the frequency, genesis location and track direction and length) are not correlated with East China landfall count. Driving climate indices including the WPSH, PMM and El-Niño related indices are not correlated with East China landfall either during or prior to the TC season. It is the steering over the East China Sea in the final stages of landfall that is most important. Anomalous geopotential height at 500 hPa over Korea and Japan was a reliable indicator of heightened landfall throughout the season. This was linked to an Easterly anomaly over the East China Sea which acts to steer TCs towards the coast. This feature was reliably present in the analysis on both seasonal and sub-seasonal scales. If this feature is predictable by numerical models, then a hybrid dynamical-statistical model could form the basis of an East China landfall forecast climate service.

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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