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LETTER

On the relationship between hurricane cost and the integrated wind profile

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Abstract

It is challenging to identify metrics that best capture hurricane destructive potential and costs. Although it has been found that the sea surface temperature and vertical wind shear can both make considerable changes to the hurricane destructive potential metrics, it is still unknown which plays a more important role. Here we present a new method to reconstruct the historical wind structure of hurricanes that allows us, for the first time, to calculate the correlation of damage with integrated power dissipation and integrated kinetic energy of all hurricanes at landfall since 1988. We find that those metrics, which include the horizontal wind structure, rather than just maximum intensity, are much better correlated with the hurricane cost. The vertical wind shear over the main development region of hurricanes plays a more dominant role than the sea surface temperature in controlling these metrics and therefore also ultimately the cost of hurricanes.

1. Introduction

Currently, there are several well-known metrics to infer the destructive potential of hurricanes, e.g., Saffir-Simpson Hurricane Scale [1] and hurricane strength [2]. The accumulated cyclone energy (ACE) and power dissipation index (PDI) have been widely used as indicators of destructive potential [3, 4], as they are able to consider the hurricane frequency, intensity and duration. The important role of sea surface temperature (SST) in hurricane intensity has been identified using PDI and ACE [4–7]. However, the limitation of these metrics is that they do not take into account the spatial extent of the hurricane wind structure, namely, any size effects.

The size effect is crucial to understanding the hurricane destructive potential and cost [8–10]. For instance, Hurricane Sandy's enormous size mainly explains its great economic loss [11]. The vertical wind shear is one of the most important atmospheric variables affecting hurricane size and wind structure evolution [12]. However, it has been unclear whether the SST or vertical wind shear plays a more important role in the ultimate damage. To answer this question we need metrics of hurricane destructive potential that take into account the hurricane intensity and wind structure at the same time. Although there have been case studies [9, 11], to date it has not been possible to conduct a comprehensive analysis because it requires continuous historical profiles of near-surface wind speed from hurricane center to an outer storm limit.

To overcome this obstacle, we use a new analytical model ('the λ model') [13] to reconstruct the historical wind profiles of all the landfalling hurricanes for 1988–2014 and correlate with damage for the first time. The λ model is highly effective because it requires no free scaling parameters. It constructs a wind profile from only the minimum surface pressure (p_{min}), the latitude (ϕ) of hurricane center and one measure of wind radius. Any of the following commonly reported measures of wind radii can be used: the radius of maximum wind (R_{max}), gale-force wind (R_{18}), damaging-force wind (R_{26}) or hurricane-force wind (R_{33}).

2. Data and methods

The hurricane records for 1988–2014 are taken from the extended best track data set [14]. It provides the wind radii records, i.e., R_{max}, R_{18}, R_{26} and R_{33}. R_{18}, R_{26} and R_{33} are measured in four quadrants. The extended best track data set covers 27 years, and is still the longest available hurricane best track data set including relatively complete size measurements. R_{18}, R_{26} and R_{33} from 2004 onwards have been post-season quality controlled [15], whereas the wind radii measurements for 1988–2003 are only operational estimated. The detailed description of the US landfalling hurricanes is taken from the National Oceanographic and Atmospheric Administration's Atlantic hurricane reanalysis project (http://www.aoml.noaa.gov/hrd/hurdat/UShurrs_detailed.html). From 1988 to 2014, there are 187 hurricanes and 41 of them made landfall 57 times along the US coast. However, due to the missing size records, Hurricane Emily is excluded in the wind profile reconstruction at landfall. The monthly SST and wind data are taken from the Hadley Center Sea Ice and Sea Surface Temperature data set [16] and the European Center for Medium-Range Weather Forecasts ERA-Interim reanalysis data set [17], respectively. In this study we only focus on the environmental factors on hurricane destructive potential, so we use a normalized hurricane cost data set [18] (http://www.icatdamageestimator.com). After normalizing the cost, the societal changes, e.g., inflation, population increase and per capita wealth increase, causing artificial increase trends have been removed [19, 20]. However, one should note that the spatial variability in the exposure along the US coast is not considered here.

The λ model [13] can be written as

$$V = \sqrt{\frac{2(p_{env} - p_{min})}{\rho}} \times \sqrt{\frac{2\lambda^2}{r^2}\left(1 - e^{-\frac{r^2}{2\lambda^2}}\right) - e^{-\frac{r^2}{2\lambda^2}}} - \frac{1}{2}fr, \tag{1}$$

where V is the tangential wind speed near the surface, r the radius from the cyclone center, ρ the air density set as 1.1 kg m^{-3}, p_{env} the pressure in the ambient environment set as 1013 hPa, f the Coriolis parameter that can be easily calculated with the latitude of hurricane center, ϕ. The λ represents the width of the Gaussian distribution of moist entropy in the boundary layer. By assuming ρ and p_{env} are constant, we can use the λ model to reconstruct historical wind profiles with observed p_{min} and ϕ if we know how to quantify λ.

Substituting a threshold wind speed (V_{th}) in equation (1), we can solve for the wind radius of V_{th} (R_{th}) analytically [13]. The analytic solution can be used to quantify λ, which can be written as

$$\lambda = \frac{R_{th}(fR_{th} + 2V_{th})}{4}\sqrt{\frac{\rho}{p_{env} - p_{min}}}. \tag{2}$$

When the near-surface wind speed in equation (1) reaches the maximum value, the numerical solution for R_{max} can be written as

$$\lambda = \frac{1}{1.89}R_{max}. \tag{3}$$

Equation (3) shows the other way to quantify λ. We only use equation (3) when comparing the reconstruction of wind profiles with the λ model to the Holland tropical cyclone wind profile model [21]. In principle combining equations (1) and (3) can be used to derive a new wind-pressure relationship, which can be written as

$$V_{max} = 0.77\sqrt{\frac{p_{env} - p_{min}}{\rho}} - \frac{1}{2}fR_{max}. \tag{4}$$

Equations (2), (3) and (4) suggest that the hurricane intensity, R_{max} and outer circulation size are related. However, one should note that there are only weak relationships found among them in the observations [2, 22, 23].

The Holland model can be written as

$$V = \sqrt{B\frac{p_{env} - p_{min}}{\rho}\left(\frac{R_{max}}{r}\right)^B e^{\left(-\frac{R_{max}}{r}\right)^B} + \frac{1}{4}r^2f^2} - \frac{1}{2}rf, \tag{5}$$

where B is a scaling parameter describing the shape of a wind profile. With observed R_{max}, p_{min} and ϕ, we reconstruct wind profiles with different B values from 1.0 to 2.5 [21] and then find the optimal B by comparing the observed and reconstructed R_{max} for every single case.

Four metrics of hurricane destructive potential are calculated. They are the PDI, ACE, integrated power dissipation (IPD) and integrated kinetic energy (IKE).

The PDI [4] is defined as

$$\mathrm{PDI} = \sum_{\tau} V_{max}^3, \tag{6}$$

where V_{max} is the maximum 1-min sustained wind at the height of 10 m and τ the lifetime of a hurricane with the maximum wind speed of at least hurricane force. τ does not include the extratropical portion of a life span. The annually accumulated PDI is calculated by summing up the PDI of all hurricanes in a hurricane season.

The ACE [3] is defined as

$$\mathrm{ACE} = \sum_{\tau} V_{max}^2. \tag{7}$$

The annually accumulated ACE is calculated by summing up the ACE of all hurricanes in a hurricane season.

The IPD [4] is defined as

$$\mathrm{IPD} = \int_S \rho C_D V^3 \mathrm{d}S, \tag{8}$$

where C_D is the drag coefficient calculated with wind speed [24] and S the integral area with the wind speed of at least gale force.

The IKE [9] is defined as

$$\mathrm{IKE} = \int_{\mathrm{D}} \frac{1}{2}\rho V^2 \mathrm{d}D, \tag{9}$$

where D is the integral volume with the wind speed of at least gale force. The integral volume D is 1 m in the vertical and centered at the 10 m level.

The PDI and ACE are the metrics calculated from the intensity only. In contrast, the IPD and IKE are the metrics based on the whole wind structure at landfall, which means the hurricane intensity and size effect are both considered. Because of the asymmetry of hurricane wind structure during landfall, equation (3) is not chosen to quantify λ for the calculation of IPD and IKE at landfall. This is because there is only one measurement of $R_{\max}$ at one time in the best track data set. Instead, we apply equations (1) and (2) using R_{th} from each quadrant to get the wind profiles. Moreover, we will discuss the uncertainty of IPD calculation, and this error analysis can only be conducted when the uncertainties of the hurricane location, intensity and size are all given. However, the uncertainty of $R_{\max}$ was not reported whereas the uncertainties of the outer wind radii (R_{33}, R_{26} and R_{18}) are available [15]. The IPD and IKE are then calculated as the sum of every quadrant. It should be noted that the λ model was originally developed as an axisymmetric model [13] based on the assumption that the azimuthally averaged moist entropy in the boundary layer is a Gaussian shape. However, in order to consider the asymmetry of hurricane wind structure during landfall, here we further assume that in every quadrant the azimuthally averaged moist entropy in the boundary layer follows a Gaussian shape.

The vertical wind shear is defined as

$$\mathrm{Shear} = \sqrt{(u_{200} - u_{850})^2 + (v_{200} - v_{850})^2}, \tag{10}$$

where u_{200}, u_{850}, v_{200} and v_{850} are the monthly means of zonal (u) and meridional (v) winds at the pressure levels of 200 and 850 hPa. The SST and vertical wind shear are computed as the mean within the main development region of hurricanes (MDR, 20°W–60° W, 6°N–18°N) for the peak months (August–October) of the hurricane season. The relative MDR SST [25] shows similar results as the absolute MDR SST, so only the absolute MDR SST is shown in the following analysis. The MDR definition follows a previous study [4] and other studies also use different areas to define MDR. The results shown in the next section are robust when using other MDR definitions.

For ease of comparison, we normalize the time series shown in the next section. The normalization formula is given as

$$n'_i = \frac{n_i - n_{\min}}{n_{\max} - n_{\min}}, \tag{11}$$

where n_i is the value in year i, n_i' the normalized value, $n_{\min}$ the minimum value and $n_{\max}$ the maximum value of the time series. After normalization all the values of a time series are scaled between 0 and 1.

3. Results

We first compare the hurricane intensity deduced from the reconstructed wind profiles to observation. The hurricane intensity is measured as the $V_{\max}$. For comparison, the extensively used Holland model is also applied. The Holland model requires one scaling parameter that can be obtained by a fitting. To evaluate the reconstruction skill, the square of Pearson linear correlation coefficient (R^2), p-value (p), root mean square error (RMSR) and bias are calculated. By using the exactly same variables ($p_{\min}$, ϕ and $R_{\max}$), the λ model performs superiorly to the Holland model (see the supplementary figure 1), with stronger correlation and smaller bias and RMSE at both the time of highest intensity ($R^2 = 0.93$, $p < 0.001$, bias $= +0.08$ m s^{-1}, RMSE $= 3.18$ m s^{-1}) and landfall ($R^2 = 0.75$, $p < 0.001$, bias $= +3.57$ m s^{-1}, RMSE $= 5.06$ m s^{-1}). The reconstruction with the λ model is also effective when replacing $R_{\max}$ with another wind radius, e.g., R_{26} (figure 1). Comparing figures 1(a) and (b) we can see that the λ model is more skilful at reconstructing wind profiles over open oceans than along the coast. This is understandable as the λ model is originally symmetric, assumes continuous entropy flux from the ocean and does not take into account the influence of land. Comparing the reconstruction at landfall using R_{18}, R_{26} and R_{33}, the λ model provides the best estimation of multiple wind radii by using R_{26} (see the supplementary figure 2 and supplementary text 1). R_{26} is thus chosen for the following analysis.

With the reconstructed wind profiles, we can now calculate two 'integrated metrics': the IPD and IKE. These integrated metrics are based on the whole wind structure at landfall so the hurricane intensity and size effect are both considered at the same time. Figure 2(a) shows that the IPD of individual hurricanes at landfall is well correlated with the normalized hurricane cost ($R^2 = 0.47$, $p < 0.001$). This is also found when using R_{18} or R_{33} to reconstruct the wind profile (see supplementary figure 3). The costliest hurricane is Hurricane Katrina with an IPD of 6.88×10^{13} m^2 s^{-3}. However, the IPD itself is only weakly related to hurricane intensity. For example, category-5 Hurricane Andrew has only 26% of the IPD of category-1 Hurricane Sandy. As shown in figures 2(b) and (c), neither maximum wind speed at landfall nor PDI correlate as well with the hurricane cost as the IPD does. In addition, when only considering the relatively costly hurricanes, e.g., those causing damage of more than US$10 Billion, the IPD ($R^2 = 0.29$, $p = 0.09$) is again clearly superior to the PDI ($R^2 = 0.08$, $p = 0.39$) and the maximum wind speed ($R^2 = 0.06$, $p = 0.49$). There is also a good correlation between the hurricane cost and the other integrated metric IKE ($R^2 = 0.42$, $p < 0.001$). For the intensity only driven metric ACE, the weak correlation ($R^2 = 0.09$, $p = 0.07$) is similar to PDI (see the supplementary figure 4).

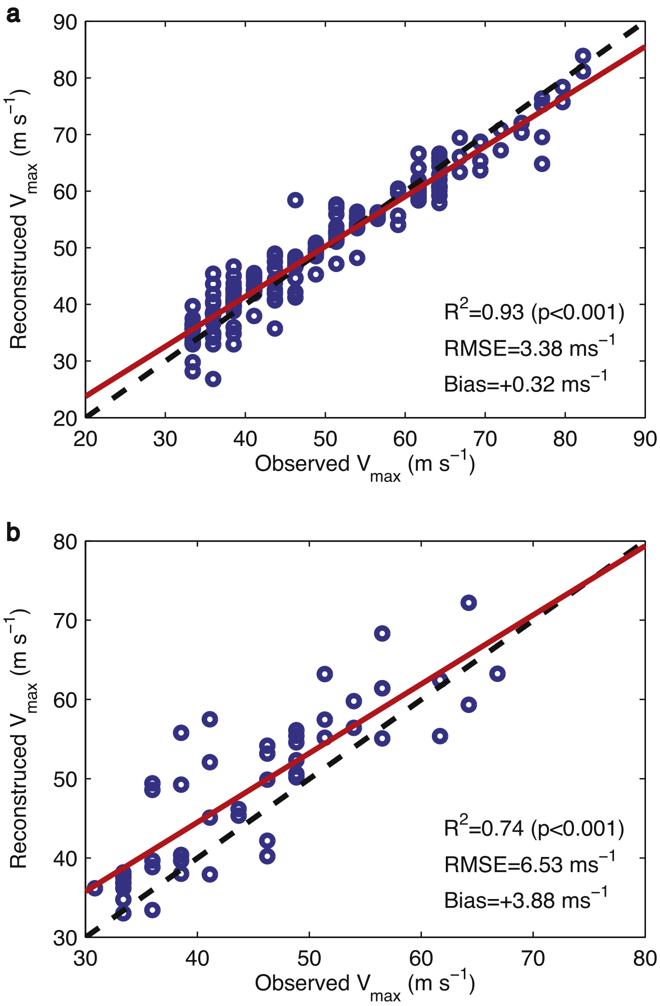

Figure 1. Comparison between the reconstructed and observed V_{max} by using the λ model and R_{26}. The largest maximum wind speed of the reconstructed wind profiles in four quadrants is regarded as the reconstructed V_{max}. (a) Comparison between the reconstructed and observed V_{max} at the time of highest intensity of 183 hurricanes for 1988–2014. (b) As in (a), but for 56 landfalls made by 40 US landfalling hurricanes. The solid red line is the linear least squares fit of the reconstructed V_{max}, and the black dashed line represents the perfect reconstruction ($y = x$).

We next compare the annually accumulated IPD at landfall to the annually accumulated PDI of all hurricanes for 1988–2014. To explain the inter-annual changes in IPD and PDI, we also show the annual variations in SST and vertical wind shear within the MDR. It is found that the annual changes in accumulated PDI and IPD are similar ($R^2 = 0.46$, $p < 0.001$). Some differences are expected as the IPD includes the size effect and landfall counts in a year whereas the PDI depends on the annual hurricane frequency and the duration of individual hurricanes. As shown in figure 3 and table 1, the SST is somewhat positively related to IPD ($R^2 = 0.14$, $p = 0.05$), but the vertical wind shear shows a remarkably stronger anti-correlation ($R^2 = 0.44$, $p < 0.001$). The significant peak of IPD around 2005 coincides with an increase in SST and a large decrease in vertical wind shear. The subsequently anti-phased changes in SST and vertical wind shear coincide with a decrease in IPD around 2007.

In terms of hurricane cost shown in figure 3, the R^2 between the annually accumulated IPD and cost is 0.66 ($p < 0.001$) whereas the R^2 between the annually accumulated PDI and cost is only 0.24 ($p = 0.01$). After excluding the years in which there are no landfalling hurricanes, the annually accumulated IPD still shows a much better correlation ($R^2 = 0.61$, $p < 0.001$) than the PDI ($R^2 = 0.30$, $p = 0.003$). Since the annually accumulated IPD shows good correlations with both inter-annual hurricane cost and environmental factors, it is plausible to establish a link between the cost and SST or vertical wind shear in the MDR directly. It is surprising that the annual hurricane cost is largely controlled by the vertical wind shear in the MDR ($R^2 = 0.28$, $p = 0.005$, table 1). In contrast, the correlation between the cost and SST is much weaker and more uncertain ($R^2 = 0.05$, $p = 0.27$). We note that there are a few outliers in certain years, e.g., 2005. After bootstrap resampling 1000 times, for example, the mean and standard deviation of the R^2 between IPD and MDR wind shear are 0.43 and 0.15 (see the supplementary table 1). The resampling analysis suggests that the good correlations

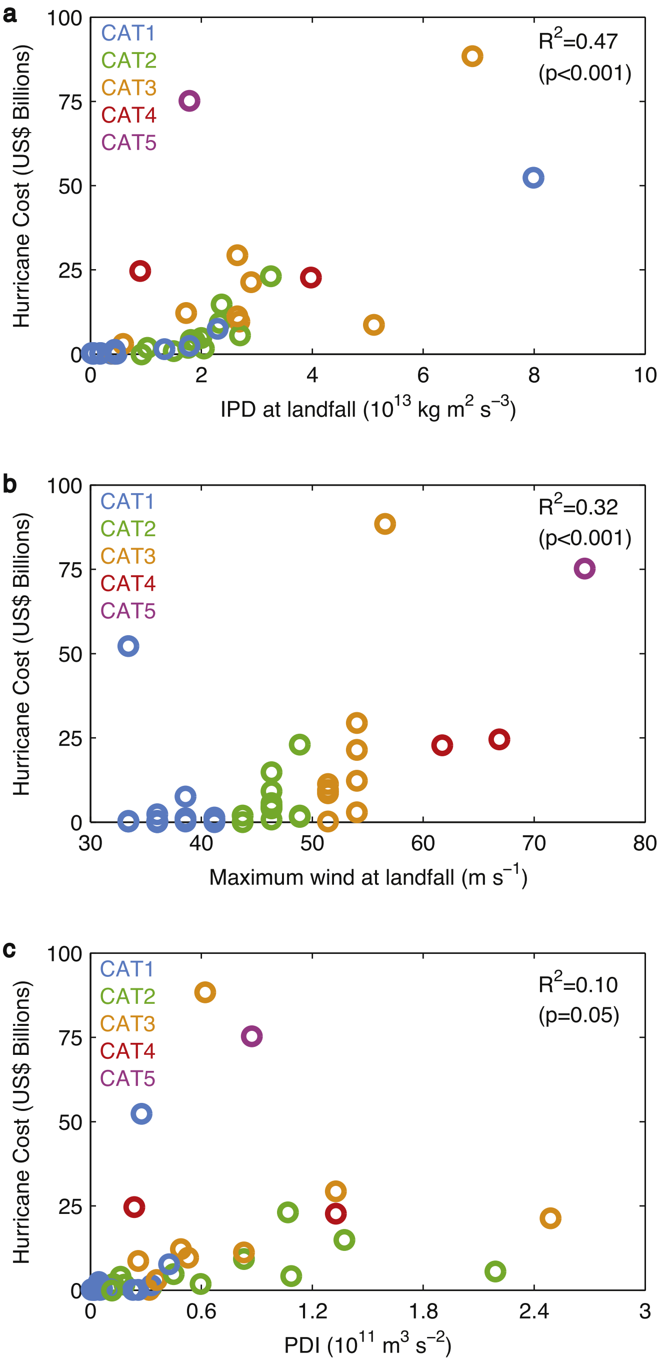

Figure 2. Comparison between the hurricane cost and metrics of hurricane destructive potential. (a) IPD at landfall. (b) Maximum wind speed at landfall. (c) PDI. The metrics are deduced from 40 US landfalling hurricanes for 1988–2014. The IPD at landfall of a hurricane is the sum of IPD from all the landfalls it makes, whereas the maximum wind speed is the maximum value of maximum wind speeds at landfall. The markers are classified into 1–5 categories (CAT) according to the Saffir-Simpson Hurricane scale [1].

between the cost, integrated metrics and MDR wind shear are not affected by the outliers.

4. Discussion and conclusions

Our results show that the wind structure at landfall is crucial to the destructive potential of individual hurricanes. The financial damage is clearly dependent on the exposure. We are not trying to determine accurate relationships between damage and the cyclone metric (e.g., a statistical model [11]), which would require exposure data, but rather show the relative importance of the wind field metrics. We then also establish the relative role of SST and wind shear to the metrics and the cost. The maximum wind speed at the landfall location is a relatively much weaker measure of the footprint, exposure and hence total damage. The intensity metrics would only be expected to outperform the integrated metrics in damage correlation, if the exposure was consistently located at or near the center of the cyclone. On average this is not the case, so it is intuitive that by considering the wind

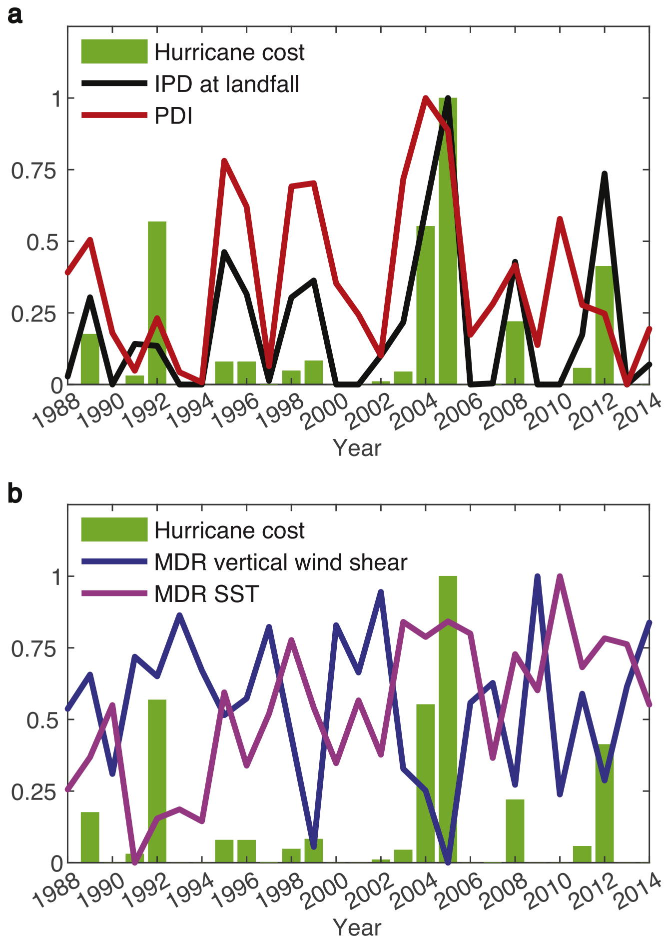

Figure 3. Variability of annually accumulated IPD, PDI, hurricane cost and MDR SST and vertical wind shear for August–October mean. The annually accumulated IPD is computed with 40 US landfalling hurricanes at landfall and the annually accumulated PDI is calculated with 187 hurricanes for 1988–2014. All the variables are normalized.

Table 1. Correlation between the annually accumulated hurricane damage, the metrics of hurricane destructive potential and MDR SST and vertical wind shear for August–October mean.

	R^2		p-value	
	SST	Shear	SST	Shear
COST	0.05	0.28	0.27	0.005
IPD	0.14	0.44	0.05	<0.001
IKE	0.14	0.45	0.05	<0.001
PDI	0.22	0.48	0.01	<0.001
ACE	0.24	0.48	0.01	<0.001

structure at landfall, the total (spatially variable) exposure is more implicitly taken into account than can be done with a single point intensity measure. Furthermore, the wind structure affects the storm surge and subsequently coastal flooding [9, 26]. It has been shown that the hurricane surge has a good relationship with R_{26} [27]. Our results suggest that the IPD and IKE capture the physical link to both the surge and the total scale of wind damage. As the hurricane damage mainly happens within 6–12 h after landfall [28], it is understandable that these two integrated metrics at landfall perform better than both the PDI and ACE throughout the lifetime and maximum wind speed at landfall. The importance of taking into account the wind structure as well as intensity has been highlighted before [8–11]. However, none of these studies compared the normalized hurricane cost with the spatially integrated measures with all the hurricane cases in the longest available data set. By conducting such a comprehensive analysis, our results give more confidence in the importance of spatially integrated measures over the intensity only measures.

In the best track data set, the mean absolute error of R_{26}, $p_{\min}$ and location relative to the average values at landfall are given as approximately 30.0%, 12.5% and 7.5%, respectively [15]. By randomly adding errors into the best track records, we can numerically assess the error propagation in the integrated metric calculation. Taking IPD as an example, the mean absolute error relative to the average IPD caused by the uncertainties in R_{26}, $p_{\min}$ and location are 56.1%, 12.7% and 0.8%, respectively. If taking into account the errors of R_{26}, $p_{\min}$ and location at the same time, the combined error of IPD is 57.6%. This means the uncertainties in the integrated metrics are mainly attributed to the errors of the size measurements.

For the inter-annual variability, table 1 shows that the hurricane cost is the most uncertain term examined. Compared to the hurricane cost, the correlations of IPD and IKE with environmental factors are both stronger and the uncertainties lower. The PDI and ACE show the best correlations and smallest uncertainties. Compared to the SST in the MDR, the vertical wind shear always shows a much stronger correlation (and less uncertainty) with the hurricane cost and all metrics. We have also investigated the relative MDR SST and find similar correlations with IPD (R^2 is equal to 0.17 for the relative SST and 0.14 for the absolute SST), supporting the dominant role of wind shear. These results suggest that the vertical wind shear in the MDR is a dominant factor that controls these metrics of annual hurricane destructive potential and therefore also the annual hurricane cost in the US. We note that a similar calculation regarding vertical wind shear and SST versus US landfalling hurricane cost was conducted for 1960–1996 in a previous study [29]. However, no significant correlation for either variable was found at that time, perhaps because of the extreme outlier of cost of Hurricane Andrew in 1992. As for 1988–2014 there are several years of similar damage to 1992 and our statistics are more stable.

It has been well documented that the Atlantic MDR vertical wind shear is significantly controlled by the El Niño-Southern Oscillation (ENSO) [30, 31]. During a La Niña (El Niño) year, the Atlantic MDR vertical wind shear is weaker (stronger), which could lead to an increase (decrease) in the annually accumulated integrated metrics at US landfall and therefore also large (small) hurricane cost. The relationship between ENSO cycle and US landfalling hurricane cost has been found from a statistical analysis [32]. To test the sensitivity of our results, we exclude all the El Niño years and find that the correlations of vertical wind shear are changed only slightly from 0.28 to 0.22 (cost), 0.44 to 0.41 (IPD), 0.45 to 0.43 (IKE), 0.48 to 0.41 (PDI) and 0.48 to 0.40 (ACE), respectively. This makes it unlikely that the good correlation between the vertical wind shear and hurricane cost is only a reflection of ENSO cycles. It thus further confirms the important role of the MDR vertical wind shear on hurricane cost.

We can only speculate on the cause of the strong dependence of the metrics and damage on the MDR vertical wind shear. One explanation could be that the mean MDR vertical wind shear for 1988–2014 is $9.10 \pm 1.00\ \mathrm{m\ s^{-1}}$ which is close to the threshold value (about $10\ \mathrm{m\ s^{-1}}$) when tropical cyclones do not form [33]. It is thus plausible that the MDR wind shear could play a more important role on the frequency of tropical cyclone genesis than the SST. However, this would not be consistent with a previous study [34] that emphasized the importance of SST over vertical wind shear in frequency of tropical cyclones. The important role of the MDR vertical wind shear on the size and intensity of the initial vortex and ultimately the size at landfall could be another physical cause.

There have been many studies on projected changes in the hurricane intensity, duration, frequency and outer size [35–38], but there have been no projections of the integrated metrics IPD or IKE that relate strongly to cost. There has been a study of the multi-model ensembles suggesting no sign in the projected wind shear in the crucial MDR [25]. However, larger increases are projected further along the typical hurricane tracks. Very recently it has been suggested that the increased wind shear in the West Pacific has overwhelmed the SST warming to cause a decrease in PDI in this region [39]. Given the crucial role of vertical wind shear in determining the cost of hurricanes and cyclones globally, more research is needed on projecting changes in the vertical wind shear and the horizontal wind field of future hurricanes.

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