Slower decay of landfalling hurricanes in a warming world

Lin Li and Pinaki Chakraborty

Fluid Mechanics Unit, Okinawa Institute of Science and Technology Graduate University,
1919-1 Tancha, Onna-son, Okinawa, Japan 904-0495

When a hurricane strikes land, the destruction of life and property is largely confined to a narrow coastal area. This is because hurricanes are fueled by the moisture from the ocean,[1–3] with the implication that hurricane intensity decays rapidly after striking land.[4,5] In contrast to the effect of a warming climate on hurricane intensification, many aspects of which are fairly well understood,[6–10] little is known of the corresponding effect on hurricane decay. Here we analyze intensity data for North Atlantic landfalling hurricanes[11] over the past 50 years and show that hurricanes decay has slowed, in direct proportion to a contemporaneous rise in the sea-surface temperature.[12] Thus, in the late 1960s, a typical hurricane lost ∼75% of its intensity in the first day past landfall; now, the corresponding decay is only ∼50%. We also show, using computational simulations, that warmer sea surface temperatures induce a slower decay by increasing the stock of moisture which a hurricane carries as it hits land. This 'storm moisture' constitutes a source of heat that is not considered in theoretical models of decay.[13–15] Additionally, we show that climate-modulated changes in hurricane tracks[16,17]

contribute to the increasingly slow decay. Our findings suggest that as the world continues to warm, the destructive power of hurricanes will extend progressively farther inland.

Hurricanes thrive on moisture. Moisture from warm tropical oceans fuels the intense winds of a hurricane heat engine.[2,3] In a warming world, the moisture supply is enhanced. Warmer oceans supply more moisture, and warmer air, owing to the Clausius–Clapeyron relation,[18] holds more moisture. As a result, we expect that the maximum intensity a hurricane can achieve over its lifetime increases.[6,9] Indeed, as the world warms, the strongest hurricanes (which, compared with the weaker ones, are less affected by impeding factors, e.g., wind shear) are getting stronger, with the most pronounced intensification seen for the North Atlantic hurricanes.[8]

Without moisture, hurricanes wither. A landfall severs[1,19,20] a hurricane from the ocean, its moisture source. Consequently, the intensity decays rapidly. (When the intensity drops below 33 m/s, the hurricane, per the Saffir–Simpson scale,[21] is termed a tropical storm; however, for simplicity, we refer to tropical storms also as hurricanes.) How might the hurricane decay rates change in a warming world? In contrast to the extensive studies of hurricanes over ocean, this question has attracted scant attention.

Decay timescale, τ

We study North Atlantic landfalling hurricanes (Fig. 1a) over 1967–2018 using the best-track database "Atlantic HURDAT2",[11] widely considered the most reliable database amongst all the ocean basins. (See Methods for further discussion on the data.) For each hurricane, we analyze the intensity, V, during the first day past landfall, the period over which the hurricane inflicts most of the destruction. Over this period, V decays exponentially:[4,5] $V(t) = V(0)e^{-t/\tau}$, where t is the time past landfall and τ, the decay timescale, is a single parameter that characterizes the rate of decay. (After the first day, $V(t)$ can no longer be characterized by a single parameter; see Methods.) The larger the τ, the slower the decay, and therefore, the stronger the hurricane. We train our focus on the variation—if any—of τ over the past half-century.

For each landfall event, we compute τ using $V(t)$; see Methods. From one event to another, the value of τ varies considerably. This value for any particular event is influenced by many factors, including non-climatic ones, such as the terrain underneath the hurricane.[4,5,22,23] To discern any potential signature of the climate on τ, we first analyze the distribution of τ at a multi-decadal timescale. In Fig. 1b, we plot the probability density and histogram of τ for two time periods, each spanning a quarter-century. In each period, the values of τ span a large range, signifying the influence of many factors on any individual event. But it is also clear that with time higher values of τ are preferentially realized.

Here we seek to understand the cause of this increase. We begin by examining the variations in τ at a multi-annual timescale. We average τ for all the landfall events in a given year and apply a 3-year smoothing, twice in a row, to this time series. (Because each value of τ in the time series is based on several events, this approach lessens the effects of non-climatic factors and random noise; at the same time, the smoothing can still preserve a sharp step response.[24]) In Fig. 1c, we plot the resulting τ time series. As expected from Fig. 1b, τ increases with time. Further, the increase is noticeably non-monotonic: the τ time series undulates about a linearly increasing trend. From this

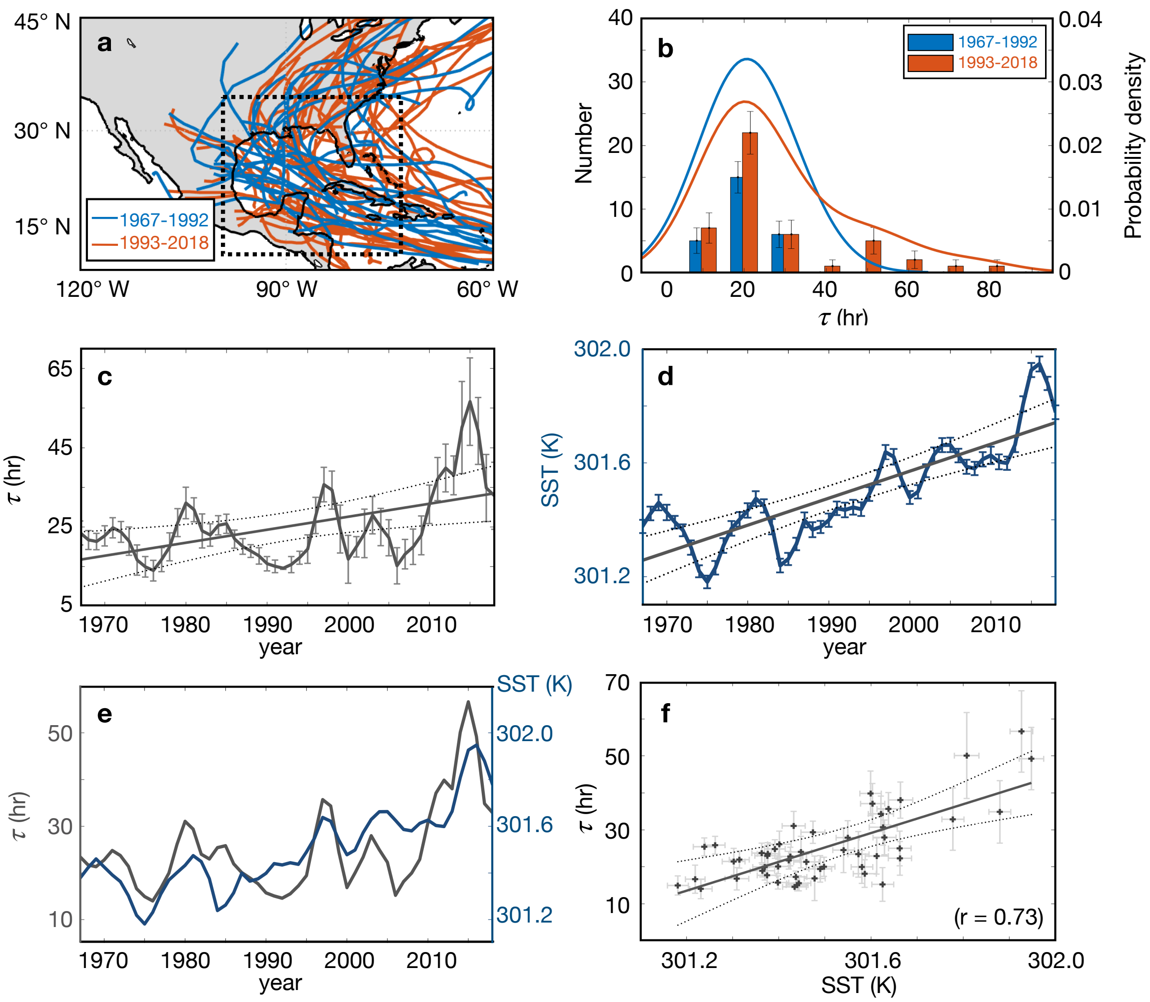

Figure 1: Effect of SST on the decay of North Atlantic landfalling hurricanes. We analyze 71 landfall events over 1967–2018 (see Methods). (a) Hurricane tracks over 1967–1992 (in blue) and 1993-2018 (in red); see panel b for the corresponding distribution of τ. The dotted box, bounded by 10^{o}N, 35^{o}N, 75^{o}W, and 100^{o}W, shows the pre-landfall region in which we compute the SST; also see Extended Data Figs. 1c,d and 2e. The map is from the MATLAB function *worldmap*. (b) Histogram and probability density of τ. The average τ increases from 21.2$\pm$1.3 hr (1967–1992, 26 events) to 28.4$\pm$2.4 hr (1993-2018, 45 events), where we also note $\pm$1 standard error of the mean (s.e.m.). The error bars in the histogram are computed using the bootstrap sampling method and correspond to $\pm$1 standard deviation (s.d.) in each bin (see Methods). (c–f) Time series of τ and SST: (c) τ vs. year (grey line); (d) SST vs. year (blue line); (e) Superposed τ vs. year (grey line) and SST vs. year (blue line); (f) τ vs. SST. Note that the τ time series echoes the SST time series; Pearson correlation r = 0.73. In panels c, d, and f, we also show the error bars (which correspond to $\pm$1 s.e.m.; see Methods), the linear regression line (solid black line), and the 95% confidence band about the regression line (dotted black lines). The increase in τ and SST over time and the relationship between τ and SST are statistically significant (at 95% confidence interval, CI) and robust to the specifics of smoothing (see Methods; Extended Data Tables 2 and 3).

linear trend we note that over the past half-century τ has increased by 94%, from 17 hr to 33 hr. Put another way, while 50 years ago the intensity one day past landfall was 24% of the landfall intensity, that figure now is 48%. (For a typical translation speed of 5 m/s, one day past landfall corresponds to a distance of 432 km inland.)

τ and sea-surface temperature

We next examine whether both the trend and multi-annual variability in the decay rate may depend on climate. As a proxy for the climate, we first analyze the sea-surface temperature, SST, using the 'HadISST' database.[12] We average the SST in time over the hurricane season, June–November, and in space over a region abutting the coastal area of landfall (Fig. 1a), and, finally, smooth using the same procedure as for the τ time series. In Fig. 1d, we plot the resulting SST vs. year, and in Fig. 1e, we superpose the τ time series and the SST time series. Notably, like the τ time series, the SST time series also undulates about a linearly increasing trend—and does so in consonance with the τ time series, with correlation r = 0.73 (Fig. 1e,f).

The foregoing analysis shows that τ and SST are reasonably well-correlated on multi-annual timescales. Next, using computational simulations, we turn our attention to the causality that underlies this correlation. We simulate landfalling hurricanes using Cloud Model 1 (CM1), a three-dimensional, non-hydrostatic, non-linear, time-dependent computational model that has been widely used to study the dynamics of idealized hurricanes;[23,25–27] see Methods. First, we simulate and contrast the fate of four hurricanes that are first allowed to develop over a warm ocean under identical conditions except for the SST (and the attendant environmental sounding). That is, SST is the sole control parameter in the simulations. The hurricanes intensify at different rates over the oceans. The warmer the ocean, the greater the moisture supply and, consequently, the faster the intensification (Fig. 2a). When their intensities reach $\approx$60 m/s, a category 4 hurricane per the Saffir–Simpson scale,[21] the hurricanes make a *complete* landfall: we instantaneously turn off the moisture flux *throughout* the bottom surface of the hurricanes.[19,20] Thereafter, we again subject the hurricanes to identical conditions.

Although the intensity at landfall is the same for all four hurricanes, their decay past landfall carries a clear signature of their development over the ocean prior to the landfall (Fig. 2a). The intensities of the hurricanes that developed over warmer oceans decay at a slower rate. In other words, echoing the field observations, τ increases with SST (Fig. 2b). But, unlike the field observations, where many factors can affect the decay, here we can unambiguously attribute the changes in τ to the attendant difference in SST.

Now we discuss *how* the SST affects the decay. Central to our considerations is the role of moisture. At this juncture, it may be instructive to consider landfall of real hurricanes for which an active source of moisture past landfall is immediately evident. At the official beginning of a landfall, the center of a hurricane moves over land. But the moisture supply still persists as roughly half of the hurricane lies over ocean. This supply continually and rapidly wanes, becoming negligible $\sim$3.5 hr past landfall (see Methods). This timescale is but a fraction of the period over which we analyze the field observations. Thus, the causal link between the SST and the decay may not stem, for the most part, from this moisture supply; also see the later discussion on translation

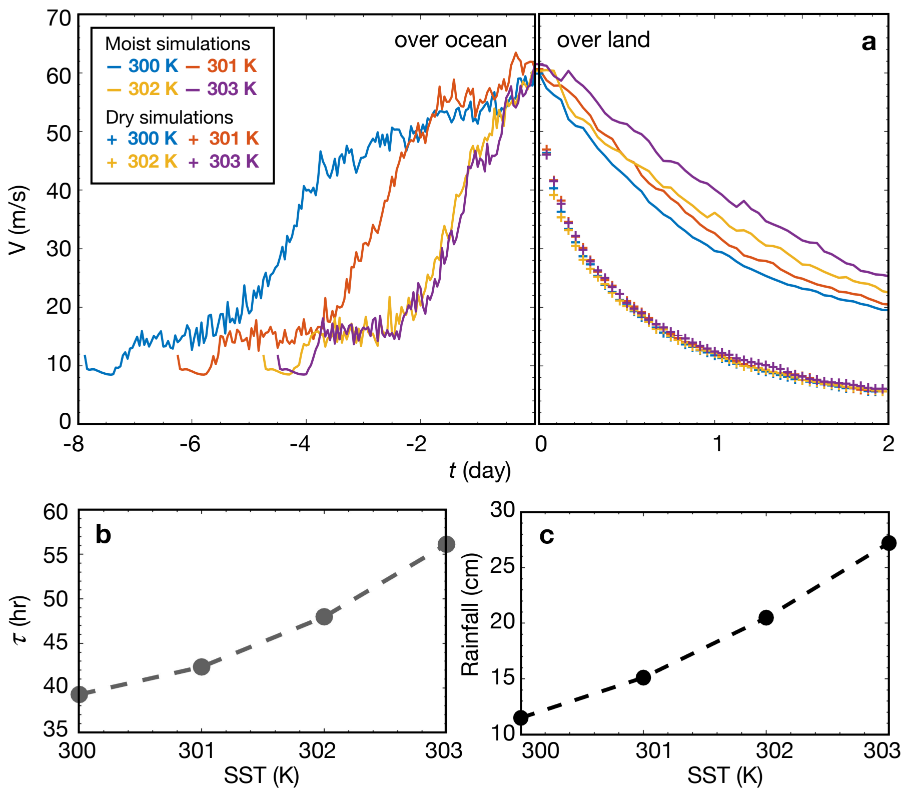

Figure 2: Effect of SST on the decay of simulated landfalling hurricanes. (a) V vs. t. For $t < 0$, the hurricanes develop over warm oceans; the different colors represent different SST. At $t = 0$, the hurricanes make landfall with $V \approx 60$ m/s (also see Extended Data Fig. 4a,b). The solid lines correspond to the moist simulations and the plus symbols to the dry simulations. (In the text, we discuss the dry simulations in the context of how the storm moisture and SST affect the decay; in Methods, we discuss the dry simulations in the context of how the hurricane size may affect the decay.) (b) τ vs. SST. Note that the values of τ are larger than those in Fig. 1c; these differences stem from the simplified setup we use for the simulations (see Methods). (c) Rainfall vs. SST. This is the total rainfall accumulated inside the radius of 100 km and over the first two days past landfall. The qualitative trend in total rainfall is not sensitive to the choice of averaging radius or time period.

speed. More starkly, in the simulated landfalls, this moisture supply is absent, and yet the effect of the SST on the decay is apparent.

To proceed, we turn our attention from an active source of moisture to one that may not be immediately evident: the 'storm moisture,' which is the moisture stocked in a hurricane during its passage over ocean and carried past landfall. We test its role by pairing each of the four simulated hurricanes discussed above with a partner. At the moment of landfall, the paired hurricanes are identical—i.e., the same velocity field, the same pressure field, the same temperature field—save for one aspect. We remove the moisture (in all phases: vapor, liquid, and ice) in the partner hurricanes. Thereafter, we evolve these dry hurricanes over land subject to the exact same conditions as their moist counterparts.

In Fig. 2a, we plot the decay for the four pairs of hurricanes. The causal role of storm moisture is now clear. The dry hurricanes decay at a notably faster rate compared with their moist partners—the storm moisture slows the decay of the moist hurricanes. Moreover, the decay rates of the dry hurricanes, unlike those of the moist hurricanes, are unaffected by their development over ocean. Indeed, the decay for the four dry hurricanes is indistinguishable. Devoid of storm moisture, SST exerts no influence on the decay of dry hurricanes. On the other hand, for moist hurricanes, the higher the SST, the greater the stock of the storm moisture, and, consequently, the slower the decay. We conclude that the storm moisture furnishes the causal link between τ and SST. A complementary aspect of this link is well known[9,28,29]—because the enhanced storm moisture eventually precipitates as rain, the rainfall from hurricanes increases with increase in the

SST (Fig. 2c).

Additional factors

Next we discuss two additional factors that, in addition to the SST, might have also contributed to the observed slowdown of the decay.

Translation speed: The translation speed of hurricanes can slow down in a warming world.[30,31] As a hurricane moves over land, a slower translation speed—specifically, its coastline-perpendicular component—allows the supply of moisture from ocean for a longer time, enhancing the storm moisture and thus promoting a slower decay past landfall. To test this potential effect, we compute the time series of the coastline-perpendicular translation speed, $v_t \cos\theta$, for the landfalling hurricanes in our study (see Methods). From the plot of $v_t \cos\theta$ vs. year, we note there is no significant change (at 95% CI) over the past half-century (Fig. 3a), and from the plot of τ vs. $v_t \cos\theta$, we note there is no significant relationship (at 95% CI) between the two (Fig. 3b). This analysis suggests that the observed increase in τ over the past half-century is unlikely to be linked with the translation speed. However, for ocean basins or time periods where there is a pronounced slowdown in $v_t \cos\theta$, its influence on τ may become discernible.

Hurricane tracks: The tracks of hurricanes can systematically shift in a warming world.[32,33] The track changes can effect changes in the decay by subjecting the landfalling hurricanes to regions of distinct τ. The regional variation can stem from factors such as the terrain[4,5,20] or the coastline shape.[34] To test for track changes and their potential effect on τ, we first consider if, similar to the poleward shift in the latitude of hurricane lifetime maximum intensity,[35] there is

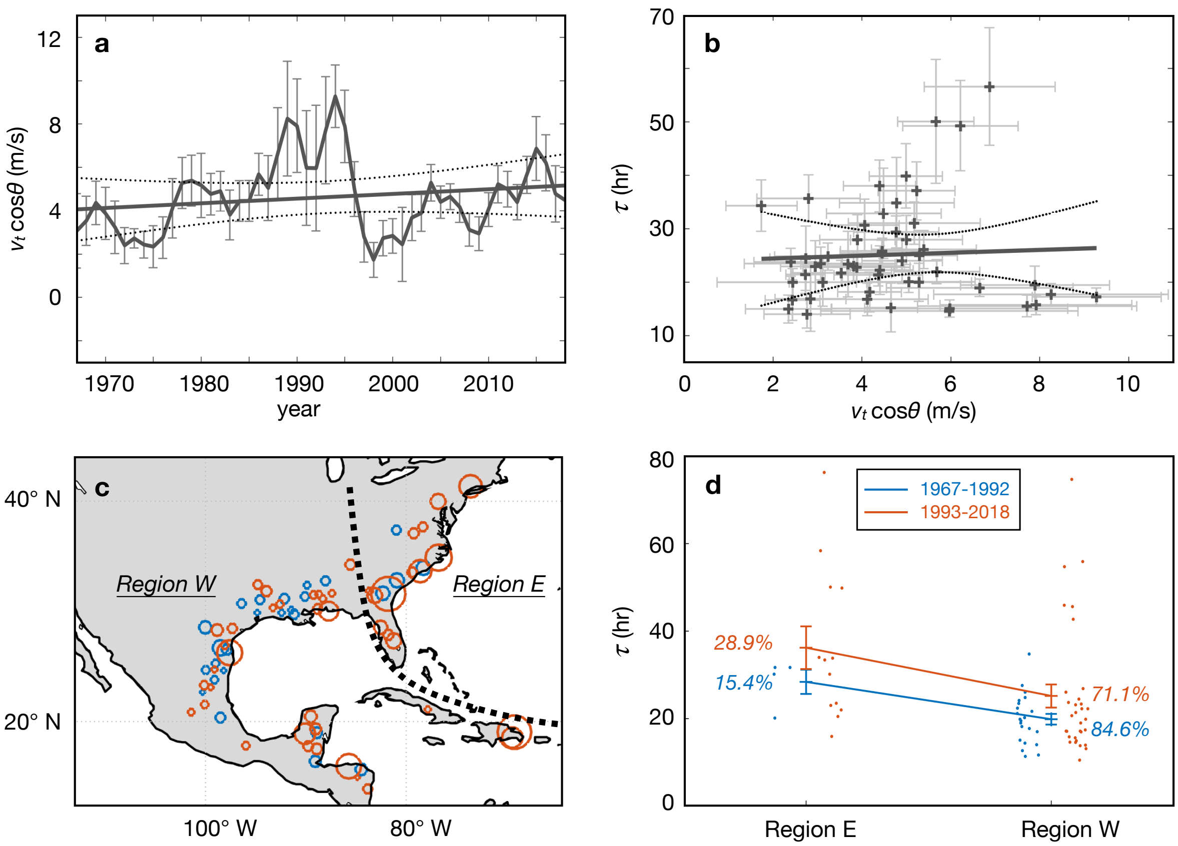

Figure 3: Effect of hurricane motion on the decay of North Atlantic landfalling hurricanes. (a, b) Effect of the coastline-perpendicular translation speed: (a) $v_t \cos\theta$ vs. year (grey line); (b) τ vs. $v_t \cos\theta$. We also show the error bars for $v_t \cos\theta$ and τ (which correspond to ± 1 s.e.m.), the linear regression line (solid black line), and the 95% confidence band about the regression line (dotted black lines). The time series of $v_t \cos\theta$ is smoothed using the same procedure as the τ time series. (c, d) Effect of the hurricane track. (c) Landfall events in region E (U.S. East Coast; the landfalls are mostly from recurving tracks) and region W (Gulf of Mexico and Caribbean; the landfalls are mostly from straight-moving tracks). Each circle marks the centroid location (see Methods) of an event (1967–1992 in blue and 1993-2018 in red), with its size proportional to the corresponding τ of the event. The map is from the MATLAB function *worldmap*. (d) τ in region E and region W and over 1967–1992 (in blue) and 1993-2018 (in red) for the 71 landfall events of our study. We also show error bars for τ (which correspond to ± 1 s.e.m.) and list the fraction of events corresponding to each region and time period. The number of events for regions E and W are, respectively, 4 and 22 (over 1967-1992) and 13 and 32 (over 1993-2018).

also a poleward shift in the latitude of the landfall events in our study (see Methods). We find no significant change (at 95% CI) in the landfall latitude over the past half-century and no significant relationship (at 95% CI) between τ and landfall latitude (Extended Data Fig. 3a,b).

Turning our attention from poleward shift, next we note that studies[16,17] of North Atlantic hurricanes report an eastward shift in their tracks. Specifically, as the climate warms, the fraction of hurricanes that make landfall on the US East Coast increases while the fraction of hurricanes that make landfall on the Gulf of Mexico and Caribbean decreases. (The corresponding tracks, based on their shapes, are termed, respectively, "recurvers" and "straight movers.") To test if the landfall events in our study also manifest a similar trend, we divide the events into two regions, region E and region W (Fig. 3c), and two (quarter-century long) time periods. We find that the fraction of the events indeed shifts towards region E with time (Fig. 3d). Further, in any given time period, the decay in region E is slower than the decay in region W (Fig. 3d), as has also been noted previously[22,36] (but the precise causes of this regional variation remain unclear). It follows that the track changes preferentially increase the fraction of the events that correspond to a slower decay and therefore contribute to an increase in τ with time. By computing the increase in τ resulting from track changes and from SST increase separately, we estimate their relative contributions to be, respectively, $\sim$21% and $\sim$79%; see Methods.

Concluding Remarks

In summary, we have shown that over the past 50 years the value of τ for North Atlantic landfalling hurricanes has increased by 94%. This increase is primarily fueled by the enhanced stock of storm moisture supplied by warmer oceans. An additional contribution stems from the climate-modulated changes in the tracks of the hurricanes. Unlike the effect of enhanced moisture, which invariably slows the decay, the effect of track changes is tied to the regional differences in the values of τ where the hurricanes make landfall. For North Atlantic landfalling hurricanes, our analysis suggests that the effect of the eastward shift in the tracks has been consonant with the effect of the contemporaneous SST increase.

As potentially promising topics for future work, we suggest: (1) study of other factors (e.g, extratropical interactions; see Methods) that may affect the decay; (2) study of landfalling hurricanes from other ocean basins (see Methods for a note of caution regarding the reliability of global data). Further, our findings call attention to the critical role of storm moisture in the dynamics of decay. However, the prevailing theoretical models of decay[13–15] treat a landfalling hurricane as a dry vortex which decays due to the frictional drag with the land underneath. Lacking moisture, these non-thermodynamic models cannot furnish any link between the climate and the decay. We submit that including moist thermodynamics as an essential component of a theoretical model of decay may help elucidate the key processes that underly the intricate dynamics of decay.

Last, we note that our findings have direct implications for the damages inflicted by landfalling hurricanes in a warming world. Even when the intensity at landfall remains the same (see, e.g., Extended Data Fig. 2c), owing to the slower decay regions far inland face increasingly intense winds (accompanied by heavy rainfall). Consequently, the incurred economic toll keeps soaring. This factor may shed new light on a puzzling trend. For over a century, the frequency and intensity of landfalling hurricanes have remained roughly unchanged,[9,37,38] but their inflation-adjusted economic losses have steadily increased.[37,38] It has been argued[37,38] that this increase stems entirely from societal factors (the growth in coastal population and wealth), with the warming climate playing no role. We submit that this accounting is possibly missing the costs tied to the slower decay of the hurricanes in a warming world. Finally, for hazard planning, we call attention to inland regions—they are less prepared for hurricanes than their coastal counterparts and therefore are more vulnerable to the damages from the slowly-decaying hurricanes.

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Methods

North Atlantic landfalling hurricanes

We analyze field data of North Atlantic landfalling hurricanes from the best-track database[11] Atlantic HURDAT2. This database provides the hurricane intensity and other parameters every 6 hours. We focus on the time period 1967–2018; we do not consider the pre-1967 data because they are less reliable.[4,39] In this period, we study all the "landfall events" (meaning, each time a hurricane makes landfall; a single hurricane may have multiple landfalls) that meet two criteria. First, at the first inland data point, $V \geq 33$ m/s, the minimum intensity for "hurricane wind" per the Saffir–Simpson scale.[21] Second, there are at least four continuous inland data points (this excludes the hurricanes whose stay over land is less than one day). (We determine the inland data using the MATLAB function *land_or_ocean*.[40]) Applying these criteria yields 75 events. Of those, we exclude one event (Hurricane Georges's 1998 landfall over Cuba) where the intensity increased instead of decaying. Further, to prevent the statistics to be skewed by outliers, we exclude 3 events where the value of the decay timescale, τ, was abnormally large (>2 s.d. above the mean value; Extended Data Fig. 2a). (Including these outliers does not qualitatively affect the results; Extended Data Fig. 2b.) By excluding these 4 events, our study comprises 71 events.

For better statistics, it would be advantageous to consider landfalling hurricanes from all the ocean basins. The intensity data from the different ocean basins, however, differ widely in reliability.[8,41] Collating data from the different basins, therefore, can introduce large noise that may obscure a climatic signature. We thus focus on the North Atlantic landfalling hurricanes, whose best-track database,[11] Atlantic HURDAT2, is widely considered the most reliable database amongst all the ocean basins.

Decay timescale, τ

For each landfall event, we compute τ from the time series $V(t)$ for $t = t_1, t_2, t_3$, and t_4, the first four synoptic times (0000, 0600, 1200, and 1800 UTC) past landfall. To this time series, we fit the Kaplan–DeMaria model of exponential decay:[4,5] $V(t) = V(0)e^{-t/\tau}$, which can be expressed as $V(t) = V(t_1)e^{-(t-t_1)/\tau}$. Specifically, we compute the best-linear-fit line to the data points plotted as $ln(V(t)/V(t_1))$ vs. $t - t_1$; the slope of this line equals $-1/\tau$ (Extended Data Fig. 1a).

Note that the original Kaplan–DeMaria model, which applies to V(t) for a period of more than one day, contains two parameters: τ and an additive constant. Over the first day, however, $V(t)$ conforms well to the exponential model with only one parameter, τ. This can be verified by computing the adjusted r^2 as the goodness of fit. For most events in our study, the adjusted $r^2 \geq 0.9$ (Extended Data Fig. 1b).

In Fig. 1b, we plot the histogram and probability density for τ. To calculate the histogram, we bin with a window of 10 hr. We also plot the error bars for the histogram, which we calculate using the bootstrap sampling method (repeated random sampling with replacement in each time series). The error bars correspond to one ± 1 s.d. in each bin. To calculate the probability density, we use the MATLAB function *ksdensity* with a window of 10 hr.

To compute the time series of τ (Fig. 1c) and of other factors, we apply a 3-year smoothing, twice in a row, using the MATLAB function *smooth* and set its option *span* equal to 3 years. We compute the corresponding s.e.m. as s.d. /$\sqrt{N}$, where N is the number of events in the 5-year window (because the smoothing used a 3-year window twice) centered on a given year. (The s.e.m. for the SST time series is computed differently; we consider the SST data from all the over-ocean grid points inside the dotted box of Fig. 1a for the hurricane seasons in any given 5-year window.) From Fig. 1c, we compute the increase in τ assuming a linear trend. It is possible that the trend is non-linear, or piecewise linear, with the increase in τ being more pronounced over the past two decades. For simplicity, we consider the linear trend.

Last, we note that the methods used to estimate the best-track value of V have steadily improved over time. For inland data, the most important of these changes is the increase in the density of weather stations. Because a denser sampling improves the odds of finding the true maximum wind speed, the recorded V gets biased towards higher values with time. Note, however, that we compute τ not using the value of V but of the ratio $V(t)/V(t_1)$. If we denote the bias in V by δV, the resulting bias in this ratio can be estimated as $\delta V(t)/V(t) - \delta V(t_1)/V(t_1)$. Consequently, τ is less sensitive to the bias than V. In particular, if $\delta V \propto V$ (see, e.g., Ref.[42]), then there is no effect of the bias on τ. While we expect that the bias does not significantly affect the τ time series, with the available data it is very difficult to precisely quantify the effect. Further, if there are appreciable differences in the methods used to estimate the different $V(t)$ for any event, its effect should also be considered. Future studies may seek to precisely quantify how changes in the methods of estimating V may affect the τ time series.

Statistical significance

We judge the relationship between two variables to be statistically significant if the two-sided, 95% CI of their slope from linear regression excludes zero (see, e.g., Ref.[30]). In computing the CI, we adjust the degrees of freedom, *d.f.*, if the time series of either of the variables has serial correlation (which we test using the Dublin–Watson test). Specifically, first we compute the decorrelation timescale from the autocorrelation of the residuals (see, e.g., Ref.[43]). For example, the τ time series is not significantly autocorrelated after 2 yr (Extended Data Table. 3b). Taking its decorrelation timescale as 3 yr, we then compute the effective *d.f.* as n/3 -2 = 15, where n = 52 is the sample size. Using the effective *d.f.*, we compute the CI. (We use the same procedure to compute the confidence bands plotted in the figures, e.g., Fig. 1c,d,f.) In Extended Data Tables 2 and 3c, we list the results of this analysis, where, for reference, we also list the uncorrected *P*-values (which we compute using the full *d.f.*).

Smoothing and robustness of results

As noted in the manuscript, we smooth all the time series to lessen the effects of non-climatic factors and random noise. Further, smoothing yields more reliable s.d. (and, therefore, s.e.m.) by increasing the number of samples per data point (Extended Data Table 3a). But, smoothing also induces serial correlation. The unsmoothed time series has either no serial correlation (e.g., SST time series) or a small decorrelation timescale ($<$2 years; e.g., τ time series). With increase in the time window of smoothing, the decorrelation timescale monotonically increases. Accounting for the decorrelation timescale, we find that the statistical significance of unsmoothed to variously smoothed time series remains robust to the the specifics of the smoothing (Extended Data Table 3c).

Computational simulations

We perform computational simulations of landfalling hurricanes using Cloud Model 1 (CM1, version 18.3).[25–27] See Extended Data Table 1 for a list of the simulation parameters.

To simulate the effect of global warming, we change the SST and the attendant environmental sounding (the vertical profiles of temperature and humidity; these profiles are based on measurements[44] over the North Atlantic ocean during the hurricane seasons of 1995-2002). The actual change in the sounding in a warming climate can be complex, but, to focus on the salient aspects, here we follow Ref.[6] and consider a simplified scenario. We modify the sounding by shifting its temperature profile (uniformly at all altitudes) to match the change in the SST and changing its humidity profile so that the relative humidity profile remains the same.[6,44] All other parameters in the sounding are kept unchanged.

To simulate a complete landfall, we set the coefficient of enthalpy, $\mathrm{C_e}$, equal to zero.[19,20] This turns off the flux of moisture (and sensible heat) from throughout the bottom surface of the hurricane. For simplicity, we keep all the other simulation parameters the same as for the hurricane over the ocean.

We calculate τ using $V(t)$. We follow the same procedure as for the field data, except now we consider the first two days past landfall. (Calculating τ using $V(t)$ over the first day past landfall yields comparable results.) This is because whereas in the field data $V(t)$ decays as $V(0)e^{-t/\tau}$ over the first day, the $V(t)$ for the simulation data is in good accord with the exponential model over the first two days; as we discuss presently, this difference is due to the simple model of surface drag in the simulations.

We conduct sensitivity tests on how τ is affected by the intensity at landfall (Extended Data Fig. 4c,d). We find that the increasing trend of τ vs. SST is qualitatively the same for hurricanes making landfall at different intensities.

We also conduct sensitivity tests on how τ is affected by the surface drag (as quantified by the coefficient of momentum, $\mathrm{C_D}$). We find that an increase in $\mathrm{C_D}$ notably reduces the value of τ, from 38 hr for the default $\mathrm{C_D}$ to 14 hr for $\mathrm{C_D} = 0.006$, but qualitatively the decay trends remain unaffected by the value of $\mathrm{C_D}$ (Extended Data Fig. 4e,f). For the simulations reported in the manuscript, we use the same surface drag for hurricane over ocean and over land. Note, however, that the surface drag over land is typically higher than that over ocean. We argue that it is due to this difference that the values of τ from the simulations are larger than those from the field observations (compare Fig. 1c and Fig. 2b).

Last, we conduct axisymmetric simulations and find that the trends for τ remain robust (Extended Data Fig. 5).

Timescale of completing landfall

We estimate the timescale of completing landfall—from when the center of a hurricane moves over land to when the supply of the moisture from the ocean underneath becomes negligible—using a simple model of landfall:

Consider an axisymmetric hurricane moving from ocean to land with a constant translation speed v_t and at an angle θ (Extended Data Fig. 7a). We denote the hurricane's effective radius of moisture supply[45,46] by R_o; for any radial location $r > R_o$, the supply of the moisture from the ocean underneath is negligible. (A typical value of R_o is $\sim 3R$, where R is the radius of maximum wind, RMW.) For $r \leq R_o$, we approximate the hurricane's surface-wind profile, $v(r)$, as the modified Rankine vortex:[47,48] $v = V(\frac{r}{R})$ for $r \leq R$ and $v = V(\frac{R}{r})^{1/2}$ for $r \geq R$, with $V(t) = V(0)e^{-t/\tau}$. The enthalpy flux due to the supply of moisture (and sensible heat) from the ocean, F_k, can be expressed by the bulk formula $F_k = \mathrm{C_e}\rho V(k^* - k)$, where ρ is the density of air, k is the specific enthalpy of air in the boundary layer, and k^* is the saturated enthalpy of air in the surface layer. Following Ref.,[6] we assume the relative humidity in the boundary layer as 75%.

Due to the shrinking contact area between the bottom of the landfalling hurricane and the ocean underneath, the moisture supply wanes over time. For the model outlined above, the timescale of completing landfall depends on the values of R_o, R, v_t, θ, and τ. (It also depends on the shape of the coastline;[22,34] for simplicity, here we consider a straight coastline.) For the typical values of $R_o = 100$ km, $R = 30$ km, $v_t = 5$ m/s, $\cos\theta = 0.9$ (Extended Data Fig. 1f), and $\tau = 25$ hr (the average value for North Atlantic landfalling hurricanes over 1967–2018), the timescale for the enthalpy flux to drop to 10% of its value over the ocean is about 3.5 hr (Extended Data Fig. 7b).

Hurricane size and decay

We have noted that SST affects the decay via the storm moisture. But SST may also affect the decay by modulating the size of a hurricane. In idealized f-plane simulations, higher SST results in larger hurricanes.[49–51] (In real hurricanes, however, the relationship between SST and hurricane size is more complex.[51]) Indeed, in our simulations, the hurricane size increases with SST—as SST increases from 300 K to 303 K, the corresponding RMW increases from 18.2 km to 22.5 km (Extended Data Fig. 6). To test if the hurricane size directly affects the decay, we consider dry hurricanes (Fig. 2a). At landfall, the size of these hurricanes, just like their moisture-laden counterparts, increases with SST. And yet, their decay past landfall is indistinguishable. This suggests that the hurricane size may not play a discernible role in influencing the decay. Note, however, that indirect effects—in particular, effects that account for how the storm moisture depends on the hurricane size—may be important to consider.

Translation speed time series

To compute the time series of the coastline-perpendicular translation speed, $v_t \cos\theta$, we first compute v_t and θ for each landfall event. We compute v_t using the coordinates of the first four inland locations tabulated in Atlantic HURDAT2.[11] (In computing τ, we used the same four locations.) v_t is the average translation speed over these locations. We compute θ using the coordinates of the first two inland locations and the local shape of the coastline (Extended Data Fig. 1e). In any given year, we average the $v_t \cos\theta$ for all events and then smooth this data using the same procedure as we employed for the τ time series. We plot the resulting $v_t \cos\theta$ time series in Fig. 3a.

Also note that, like the $v_t \cos\theta$ time series, there is no significant change (at 95% CI) in v_t time series (which we compute using the same procedure as the $v_t \cos\theta$ time series) over the past half-century (Extended Data Fig. 3e). Over this time period, previous studies (see Fig. 3a in Ref.,[30]

Fig. 1d in Ref.,[52] and Fig. 3b in Ref.[31]) also show no significant change in v_t. Finally, over this time period, there is no significant relationship (at 95% CI) between τ and v_t (Extended Data Fig. 3f).

Latitude time series

For each landfall event, we compute the centroid of the first four inland locations tabulated in Atlantic HURDAT2.[11] In any given year, we average the latitudes of the aforementioned centroids for all events and then smooth this data using the same procedure as we employed for the τ time series.

Hurricane tracks and decay

We analyze the effect of track changes on τ by dividing the landfall events into two regions (E and W) and two time periods (1967–1992 and 1993-2018); Fig. 3c,d. (With our sample size, 71 events, it is difficult study the spatio-temporal variation of τ at a finer scale. For example, increasing the number of regions or time periods from two to three and plotting the data as in Fig. 3d results in overlapping error bars for τ.) The overall τ for both regions taken together is 21.2 hr for the first period and 28.4 hr for the second period (Fig. 1b)—the increase is 7.2 hr. This increase has contributions from both track changes and SST increase. Next we estimate their relative contributions using Fig. 3d.

In the first period, τ = 28.4 hr for region E and 19.9 hr for region W. The respective fractions of the events are 15.4% and 84.6%. From the first to the second period, the value of τ in both regions increases (36.2 hr in region E and 25.2 hr in region W). The increase may be attributed to the contemporaneous increase in the regional SSTs. Had the hurricane tracks remained unchanged, the fraction of events would have remained the same. In this scenario, we can compute the overall τ resulting from SST increase as the weighted average 15.4% x 36.2 hr + 84.6% x 25.2 hr = 26.9 hr. But, because of the track changes, the fraction of the events shifts eastward (28.9% in region E and 71.1% in region W). As a result, the contribution of region E increases, and the overall τ becomes 28.4 hr. Thus, in the 7.2 hr increase in τ from the first to the second period, the SST increase contributes 26.9 hr - 21.2 hr = 5.7 hr, or 79%, and the track changes contribute the remainder, 28.4 hr - 26.9 hr = 1.5 hr, or 21%.

The relative contributions of SST increase and track changes on τ may also be estimated using a different approach: partial correlation.[53] If we do not divide the events into distinct regions, we can study the effect of the track changes at a multi-annual timescale. We compute the longitude time series for the centroids of the event locations by following the same procedure as we employed for the latitude time series. In accord with the above analysis, the longitude time series shows a significant eastward shift (at 95% CI) over the past half-century (Extended Data Fig. 3c). Further, there is a significant relationship (at 95% CI) between τ and longitude; correlation = -0.62 (Extended Data Fig. 3d). And, as we have discussed in the manuscript, there is a significant relationship (at 95% CI) between τ and SST; correlation = 0.73 (Fig. 1f). Finally, longitude and SST are not independent—there is a significant relationship (at 95% CI) between them; correlation = -0.59 (Extended Data Table 2). To estimate the relative contributions of SST and tracks, we use the aforementioned values of correlations and find the partial correlation between τ and longitude (with SST held constant) = -0.34 (with P-value $< 10^{-4}$) and the partial correlation between τ and SST (with longitude held constant) = 0.57 (with P-value $\approx 10^{-2}$). Thus, in accord with the analysis of Fig. 3d, the relative magnitudes of the two partial correlations suggest that the primary contribution to the increase in τ stems from the SST increase, with an additional contribution from the track changes. Also note that the τ–longitude relationship, unlike the τ–SST relationship, is not significant (at 95% CI) when both variables are detrended (Extended Data Table 2). Thus, the τ–longitude relationship is largely manifest in the long-term trend rather than the multi-annual variability, whereas the τ–SST relationship extends to both.

Extratropical interaction and decay

An extratropical interaction can affect the decay of a landfalling hurricane. This interaction can cause the hurricane to undergo an extratropical transition.[54] Here we undertake a preliminary analysis of whether our results concerning the τ time series are affected by extratropical transitions. Of the 71 landfall events of our study, Atlantic HURDAT2 marks 5 as having undergone an extratropical transition within the first day past landfall. We exclude these events and recompute the τ time series. We find that excluding the landfalls with the extratropical transitions leaves the results largely unaffected (Extended Data Fig. 2d).

More broadly, an extratropical interaction can affect the decay without an extratropical transition. Consider, for example, the interaction with the jet stream. A recent analysis[55] showed that, over the past 4 decades, the vertical shear attendant to the North Atlantic jet stream has been increasing, which, in turn, is caused by changes in the climate. If a landfalling hurricane interacts with the jet stream, the increased wind shear will cause its intensity to decay rapidly. The overall effect on τ will be mediated by the details of the interaction, which are complex and difficult to study. Future studies may shed new light on the effect of such extratropical interactions on the decay of landfalling hurricanes.

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Data availability

Hurricane intensity: The ‘Atlantic HURDAT2’ database is available at

www.nhc.noaa.gov/data/

SST: The ‘HadISST’ database is available at climatedataguide.ucar.edu/climate-data/sst-data-hadisst-v11

Source Data: The data for intensity and other parameters for the 71 landfall events of our study and the data that corresponds to the τ time series and the SST time series plotted in Fig. 1 are included in the Source Data.

Code availability

The Cloud Model 1 (CM1) source code is available at

http://www2.mmm.ucar.edu/people/bryan/cm1/

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Author contributions

L.L. and P.C. conceived the study; L.L. analyzed the field data; L.L. conducted the computational simulations and analyzed the data; L.L. and P.C. discussed the results; P.C. wrote the manuscript with input from L.L.; P.C. supervised the research.

Competing interest declaration

The authors declare no competing interests.

Corresponding author

Correspondence to Pinaki Chakraborty (pinaki@oist.jp)