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Key Points:
- Genesis indices that skillfully diagnose Atlantic basin tropical cyclone count show no relationship with U.S. hurricane landfall variance
- A Landfall Diagnostic Index is proposed as a better method than genesis indices to study tropical cyclone impacts on human populations
- This index hints that Atlantic tropical cyclone development favorability is in tension with steering patterns conducive to U.S. landfalls

Supporting Information:
- Supporting Information S1
- Figure S1
- Figure S2
- Figure S3

Correspondence to:
R. E. Truchelut,
ryan@weathertiger.com

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Diagnosing United States hurricane landfall risk: An alternative to count-based methodologies

Erica M. Staehling[1] and Ryan E. Truchelut[2,1]

[1]Research and Development Division, WeatherTiger, LLC, Tallahassee, Florida, USA, [2]Department of Earth, Ocean, and Atmospheric Science, Florida State University, Tallahassee, Florida, USA

Abstract Assessing hurricane landfall risk is of immense public utility, yet extant methods of diagnosing annual tropical cyclone (TC) activity demonstrate no skill in diagnosing U.S. hurricane landfalls. Atlantic TC count itself has limited skill, explaining less than 20% of interannual variance in landfall incidence. Using extended landfall activity and reanalysis data sets, we employed empirical Poisson modeling to produce a landfall diagnostic index (LDI), incorporating spatially and temporally averaged upper level divergence, relative sea surface temperature, meridional wind, and zonal shear vorticity. LDI captures 31% of interannual variability of U.S. hurricane landfalls and offers physical insight into why indices that successfully capture TC activity fail to diagnose landfalls: there is inherent tension between conditions likely to steer hurricanes toward the U.S. and conditions favorable for TC development. Given this tension, attempting to diagnose, predict, or understand TC count is inadequate for quantifying societal impacts due to landfalling hurricanes.

1. Introduction

Understanding the landfall risks presented by tropical cyclones (TCs) is of utmost importance to scientists, policymakers, emergency managers, insurers, and coastal citizens, with substantial social and economic implications [*Landsea et al.*, 1999; *Emanuel et al.*, 2012]. TCs are the costliest natural hazard to the U.S., totaling economic damages of approximately $500 billion across 94 separate landfall events in the past quarter-century [*Saunders and Lea*, 2005; *Aon Benfield Impact Forecasting Group*, 2014]. Since TC genesis events are a necessary precursor to coastal landfall, a common assumption is that elevated TC activity implies greater potential for disaster [*Goldenberg et al.*, 2001]. As such, over the past four decades, several research groups have pursued both predictive and diagnostic approaches to understanding the interannual variance of aggregate measures of seasonal TC activity in the Atlantic basin.

From a conceptual perspective, diagnostic methods are of particular interest, as they have the potential to provide physical insight into the mechanisms underlying seasonal variance and serve as proxies for shifts in TC activity in climate change simulations in situations where only large-scale fields are available due to computational limitations [*Ryan et al.*, 1992; *Royer et al.*, 1998; *Camargo et al.*, 2007a, 2007b; *Camargo et al.*, 2014]. Genesis indices (GIs) identify contemporaneous large-scale environmental factors to diagnose annual, seasonal, and spatial variability in TC climatology [*Menkes et al.*, 2012]. The first empirical GI to condense multiple oceanic and atmospheric fields into a single metric that expresses the relative permissibility of cyclogenesis was introduced by *Gray* [1979], and there has been renewed interest in the development of such indices in recent years with the expanded availability of high-quality atmospheric reanalysis data sets.

Traditional GIs are optimized to diagnose overall activity. Although TC count and intensity have energetic and moisture implications for the atmospheric system at large, it is landfall activity that has direct impacts on human populations and the coastal environment. While several predictive studies of U.S. hurricane landfall activity exist in the literature and have enjoyed limited success [*Lehmiller et al.*, 1997; *Saunders and Lea*, 2005; *Elsner and Jagger*, 2006], analogous approaches to diagnose landfalls are rare [*Tolwinski-Ward*, 2015], with no extant research utilizing full four-dimensional historical atmospheric data.

In this study, we investigate the utility of adapting and expanding the GI methodology to historical records of U.S. hurricane landfall. In section 2, we quantify and compare the skill of modern GIs in diagnosing Atlantic TC counts as well as in diagnosing U.S. hurricane landfalls. In section 3, we describe our methods for developing a landfall diagnostic index (LDI) and subsequently evaluate and physically interpret the results in section 4. We conclude in section 5 with a summary discussion of these findings' implications for future studies of TC risk variance.

2. Quantification of the Diagnostic Skill of Existing Genesis Indices

In the past decade, researchers have introduced five major GI diagnostic metrics of TC activity [*Camargo et al*., 2007a, 2007b; *Emanuel*, 2010; *Tippett et al*., 2011; *McGauley and Nolan*, 2011; *Bruyère et al*., 2012], each incorporating distinctive model formulations and physical inputs. While the existing literature presents compelling arguments for the utility of each individual GI, there have been few overarching efforts to objectively compare the performance of all extant GIs relative to one another, particularly in the economically sensitive North Atlantic basin [*Menkes et al*., 2012]. Here we rigorously compare the fidelity of all five modern GIs; first, in terms of the measures of aggregate TC activity variability they were designed to capture and subsequently for historical U.S. hurricane landfall activity.

This validation process requires high-quality sources of TC climatological records, as well as historical atmospheric and oceanic data. We used TC position, intensity, and landfall data from the HURDAT2 data set [*Landsea and Franklin*, 2013], as archived in version v03r07 of the International Best Track Archive for Climate Stewardship (IBTrACS) [*Knapp et al*., 2010]. While this data set is known to be missing some open ocean TCs prior to the start of the satellite era in 1966 [*Vecchi and Knutson*, 2011; *Truchelut and Hart*, 2011] as well as to underrepresent weak, short-lived TCs through the end of the twentieth century [*Landsea et al*., 2010; *Villarini et al*., 2011], the record of landfalling TCs in the continental U.S. is considered complete beginning in 1900 [*Landsea et al*., 1999]. We focus on U.S. hurricane landfalls as a proxy for societal impacts in this study, because the majority of TC economic damage is due to high-intensity landfalling events [*Emanuel*, 2011]. We constructed the annual landfall count series for 1900–2015 from U.S. hurricane landfall points in the HURDAT2 data set, supplementing with events from the Atlantic Oceanographic and Meteorological Laboratory hurricane landfall list [*Atlantic Oceanographic and Meteorological Laboratory*, 2016] for years in which HURDAT revisions have not been completed and for instances in which the center of circulation did not directly cross the coastline. Because it is the diagnostic quantity on which all extant GI methodologies were trained, we used annual Atlantic TC count as the proxy for overall activity in validating the GIs and constructed this time series for 1966–2015 by including all subtropical and tropical storms and excluding unnamed tropical depressions.

As our source of atmospheric fields, we used the NOAA/Cooperative Institute for Research in Environmental Sciences twentieth Century Reanalysis version 2 (20CRv2) [*Compo et al*., 2011]. The 20CRv2 is the first product to make global reanalysis data available for years prior to systematic upper level monitoring using a temporally stable methodology by exclusively assimilating surface observations. We obtained oceanic data from the Extended Reconstructed Sea Surface Temperature database, version 3b (ERSST.v3b), which was generated from the mid-nineteenth century to present using in situ sea surface temperature (SST) data [*Smith et al*., 2008]. These atmospheric and oceanic records overlap with the reliable U.S. landfall climatology between 1900 and 2012, affording us a temporal domain more than twice that of previous GI studies.

We used the reanalysis and SST data to calculate mean monthly values of all five modern GIs in accordance with their associated methodologies (see Text S1 in the supporting information). We then performed single Poisson regressions of Atlantic basin and extended main development region (EMDR) averages of each contemporary GI onto seasonal Atlantic TC count and U.S. hurricane landfall count. July through October (JASO) temporal averages outperformed the August through October averaging used to train several of the GIs, so we used JASO means of all GIs to more fairly represent optimized performance of extant GIs within the context of this study.

Although there is a significant positive correlation between Atlantic TC count and U.S. hurricane landfall count in the satellite era ($R^2 = 0.17$, and $P = 0.003$; see Figure S1 in the supporting information), it is clear from Table 1 that while most GIs show skill in diagnosing TC activity, they are not useful proxies for U.S. landfall incidence. EMDR-averaged GIs explain about half of the interannual variance in Atlantic TC activity, with GPI from *Emanuel* [2010] diagnosing 58.7% of the variability in annual TC count ($P = 0.005$, and $n = 47$). In contrast, there is no significant correlation evident between any GI and U.S. hurricane landfall count. Significance of values in Table 1 were calculated using Wilcoxon signed rank tests relative to climatological residuals from the mean value of the predictands with a 95% confidence threshold [*Wilcoxon*, 1945; *Wilks*, 2006].

We repeated this methodology for spatial averages of the individual components that comprise the GIs (see Table S1 in the supporting information). Of these constituent fields, relative SST (rSST) [*Vecchi and Soden*, 2007] has the strongest correlation with both Atlantic TC and U.S. hurricane landfall count, so we included it in

Table 1. Coefficients of Determination Between GIs and Annual Atlantic TC Count and U.S. Hurricane Landfalls

		TC Count (1966–2012)		U.S. Hurricane Landfalls (1900–2012)	
Genesis Index	Reference	Atlantic	EMDR	Atlantic	EMDR
Genesis Potential (GP)	*Camargo et al*. [2007a, 2007b]	0.50[a]	0.59[a]	0.01	0.01
Genesis Potential Index (GPI)	*Emanuel* [2010]	0.14	0.59[a]	0.00	0.00
Tropical Cyclone Genesis index (TCG)	*Tippett et al*. [2011]	0.51[a]	0.51[a]	0.04	0.03
Genesis Frequency Index	*McGauley and Nolan* [2011]	0.01	0.01	0.00	0.00
Cyclone Genesis Index	*Bruyère et al*. [2012]	0.24	0.39	0.00	0.00
Relative SST (rSST)	*Vecchi and Soden* [2007]	0.41[a]	0.51[a]	0.04	0.05[a]

[a]The coefficient of determination is statistically significant at the 95% level.

Table 1. Notably, rSST outperforms several GIs in capturing the interannual variability of TC count, and EMDR-averaged rSST is the only entry in Table 1 to show significant covariance with hurricane landfalls ($r = 0.22$, and $P = 0.04$), albeit explaining less than 5% of observed annual variability. This test demonstrates that while modern GIs skillfully diagnose aggregate features of climatological Atlantic TC activity, none of these indices are adequate proxies for U.S. hurricane landfall risk.

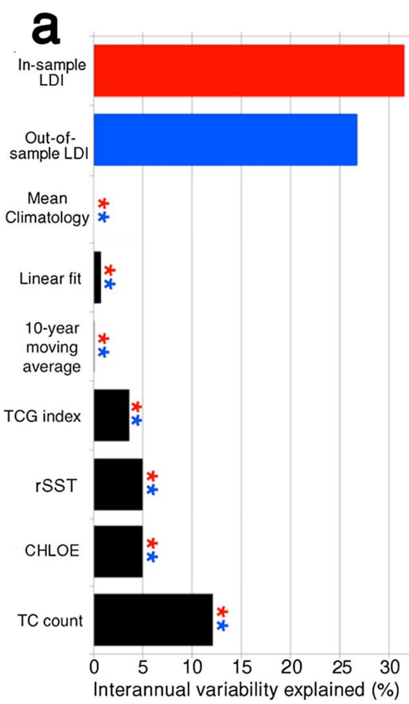
3. Landfall Diagnostic Index Construction Methodology

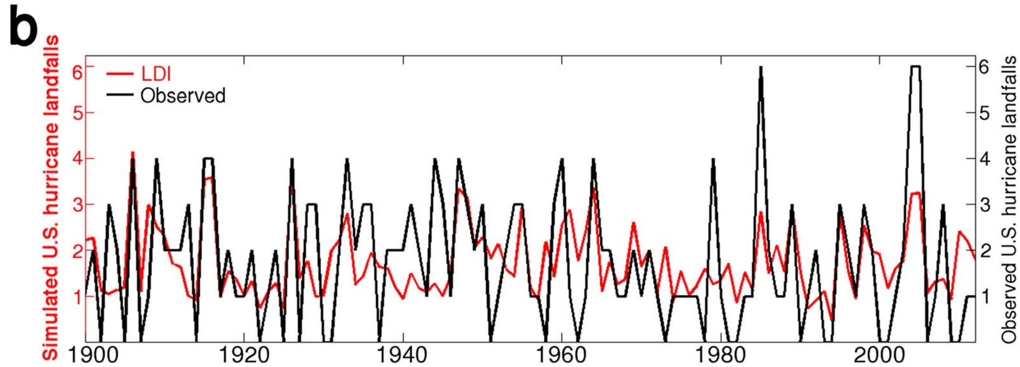
The notable lack of skill of GIs and the limited skill of TC count in capturing the interannual variance of annual U. S. hurricane landfall incidence points to the importance of factors other than overall activity in diagnosing landfall risks to coastal regions, including genesis location [*Kossin et al*., 2010], intensification processes [*Emanuel*, 2005], and large-scale steering patterns [*Saunders and Lea*, 2005]. To address this evident utility gap, we built upon the objective and methodical index generation technique described by *Tippett et al*. [2011] to produce LDI, using annual U.S. hurricane landfall events as the diagnosed quantity and considering additional potential components related to large-scale steering patterns.

We identified an expanded group of prospective LDI components from the 20CRv2 and ERSST.v3b data sets, including 255 normalized fields derived from vertical layers in the reanalysis ranging from 1000 to 100 hPa, averaged temporally over JASO and averaged spatially over 90°–40°W, 10°–40°N, excluding land areas and the Pacific Ocean (see Table S2 in the supporting information). To select the components of LDI, we used a hybrid manual-automated forward linear Poisson regression model framework (see Figure S2 in the supporting information). Using this hybrid method, we added terms to the model one at a time, making selections based on objective measures of interannual and intraseasonal diagnostic power as measured by adjusted coefficients of determination. We considered both the sign and amplitude of the correlation coefficient for each potential additional field in light of known TC genesis, steering, and intensity regulating processes, in order to make sure the resulting LDI is physically meaningful. In the initial step, we correlated the potential component fields directly with U.S. hurricane landfall count; in subsequent steps, we correlated with the residuals between the fitted response variable of the provisional LDI and U.S. hurricane landfall count (see Figure S3 in the supporting information). After we added a term to the model, we removed other fields of a similar type from the component set and regressed the remaining potential predictors onto the provisional LDI. The process ended when no potential predictors further increased the adjusted coefficient of determination between the annual LDI and U.S. hurricane landfall climatological time series. The final normalized LDI equation is

$$\mathrm{LDI} = \exp\left(0.45 + 0.47(\nabla_h \cdot v)_{250-100\ \mathrm{hPa}} - 0.22(v)_{650-500\ \mathrm{hPa}} - 0.10(\partial u/\partial y)_{1000\ \mathrm{hPa}} + 0.06(\mathrm{rSST})\right). \quad (1)$$

LDI includes four predictor terms: upper tropospheric horizontal divergence ($\nabla_h \cdot \boldsymbol{v}$) between 250 and 100 hPa (the difference in vertical motion between these levels), meridional wind (v) averaged over 500–650 hPa, zonal shear vorticity ($\partial u/\partial y$) at 1000 hPa, and rSST. The signs of the coefficients are physically apt, as anomalously positive (negative) meridional wind and positive (negative) shear vorticity correspond to offshore (onshore) steering patterns, and thus smaller (larger) potential for landfall [*Saunders and Lea*, 2005], communicated by the negative coefficient. Likewise, anomalously positive (negative) upper level divergence is associated with rising (falling) motion, while positive (negative) rSST is associated with enhanced (degraded) environmental potential, resulting in larger (smaller) potential for development and subsequent





c

Hurricane season	LDI diagnosed U.S. landfalls	Observed U.S. landfalls
1906	4.14	4
1926	3.64	4
1916	3.58	4
1915	3.53	4
1964	3.36	4
1947	3.33	4
2005	3.24	6
2004	3.23	6
1948	3.15	3
1908	2.98	1
1955	2.92	3
Decile mean	3.37	3.91

d

Hurricane season	LDI diagnosed U.S. landfalls	Observed U.S. landfalls
1994	0.46	0
1925	0.71	0
1991	0.73	1
1922	0.74	0
1982	0.85	0
1974	0.88	1
1914	0.90	0
1992	0.91	2
2009	0.93	0
1957	0.93	1
1940	0.94	2
Decile mean	0.82	0.64

Figure 1. Historical performance of LDI measured against observations and baseline diagnostic methods over 1900–2012. (a) Percentage of interannual variance (R^2) in U.S. hurricane landfall count explained by in-sample LDI (red), out-of-sample LDI (blue), and baseline climatological measures (black). Red and blue asterisks indicate a significant difference at a 90% confidence threshold between the absolute residuals of the given baseline and those of the in-sample and out-of-sample LDI, respectively, using a Wilcoxon signed rank test. (b) Interannual variability of in-sample LDI (red) and U.S. hurricane landfall count (black). Continental U.S. hurricane landfall activity and LDI for (c) highest and (d) lowest decile of LDI years.

landfall [*Garner et al.*, 2009; *Zhao and Held*, 2012], communicated by the positive coefficient. Since we normalized each time series prior to regression, the magnitudes of term coefficients also reveal the sensitivity to proportional changes in each component. LDI is therefore most sensitive to changes in the mean divergence, followed by meridional wind, zonal shear vorticity, and finally, rSST in the western Atlantic basin.

4. Results

LDI captures 31.4% of the climatological interannual variability and 71.0% of the intraseasonal variability in U.S. hurricane landfall count, with $P = 0.001$ and $P = 1.8 \times 10^{-54}$, respectively. As a check against overfitting, we performed cross-validation tests [*Elsner and Schmertmann*, 1994], comparing both in-sample and out-of-sample LDI performance against seven baseline diagnostic methodologies. We produced the out-of-sample LDI by removing 1 year from the Poisson regression, calculating values of the LDI coefficients from the remaining years, and then applying the coefficients to the predictor data of the held-out year, iterating to produce an out-of-sample expected value of landfalls over all years, 1900–2012.

Coefficients of determination between U.S. hurricane landfall count and in-sample LDI, out-of-sample LDI, and the baseline diagnostics (see Text S2 in the supporting information) are shown in Figure 1a. The baseline diagnostics include the constant mean count of annual hurricane landfalls, a linear fit regressing year onto landfall count, and a 10 year trailing average motivated by the observation that some measures of TC activity demonstrate variance on decadal scales [*Landsea et al.*, 1999; *Kerr*, 2000]. We also included annual time series of TCG and rSST values as baseline diagnostics, because they have the highest correlation with hurricane landfall count among the metrics tested, as shown in Table 1. Along with GIs, regressions using climatic indices as predictors are commonly formulated to predict or diagnose landfall activity [*Elsner and Jagger*, 2006; *Tolwinski-Ward*, 2015], so we calculated a Climatic Hurricane Landfall Odds Estimator (CHLOE) to use as our penultimate baseline method. CHLOE is a log-linear regression model that incorporates seasonally averaged Atlantic Multidecadal Oscillation [*Enfield et al.*, 2001], extended multivariate

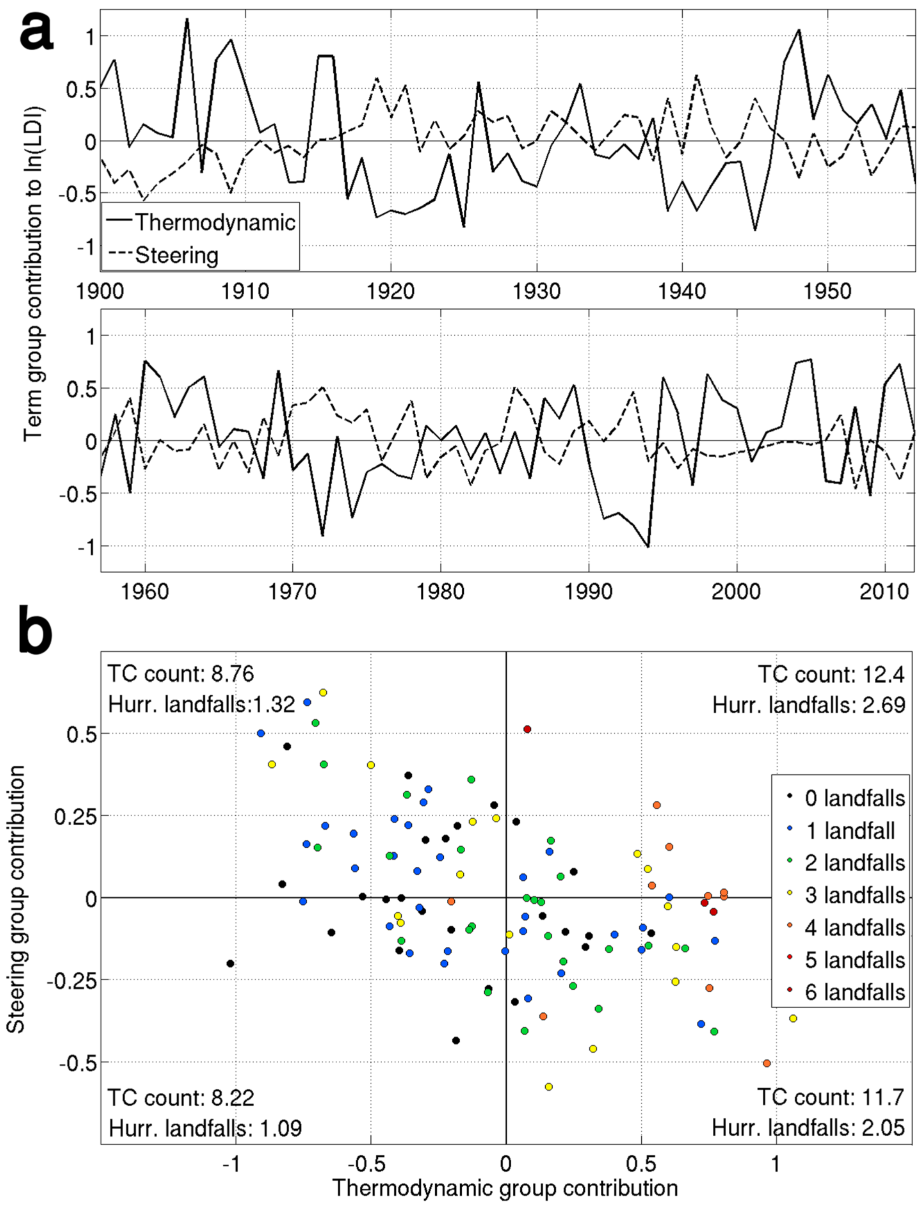


Figure 2. Behavior of LDI component groups. (a) The interannual variation of the thermodynamic (solid; divergence and rSST) and steering (dashed; meridional wind and zonal shear vorticity) term group contributions to ln(LDI). (b) Scatterplot of the contributions of the two term groups, with contribution due to steering terms on the ordinate and thermodynamic terms on the abscissa. Average TC count and U.S. hurricane landfall count for the years in each quadrant are shown in the respective corners.

El Niño–Southern Oscillation index [*Wolter and Timlin*, 2011], and North Atlantic Oscillation (NAO) [*Jones et al.*, 1997] values.

We chose the annual count of Atlantic TCs as the final baseline diagnostic. Although an average of one to two mostly short-lived TCs per year are very likely missing from portions of the climatological record [*Vecchi and Knutson*, 2011; *Truchelut et al.*, 2013], TC count over 1900–2012 shows significant skill in diagnosing U.S. hurricane landfalls where GIs do not ($R^2 = 0.12$, and $P = 1.7 \times 10^{-4}$). As Atlantic TCs are a necessary but not sufficient condition for landfalls, a methodology able to outperform TC count must do so by drawing skill from information on genesis location, intensification, or steering patterns, offering insight into the physical processes that influence seasonal landfall risk.

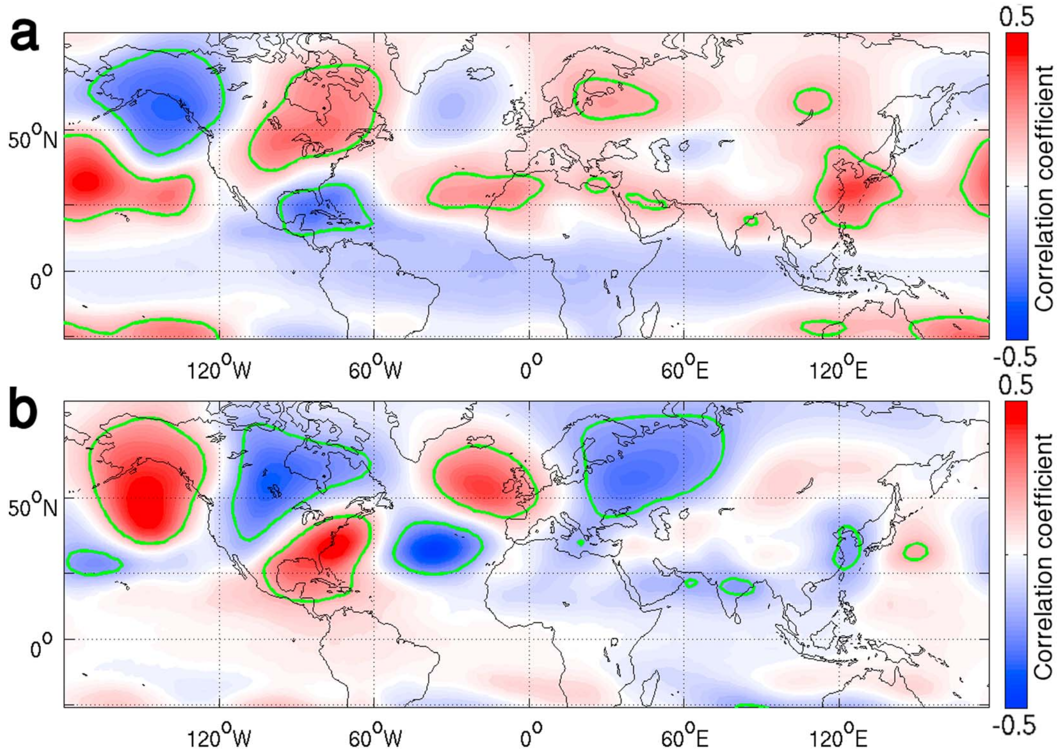


Figure 3. Relationship between LDI component groups and global circulation patterns. Correlation coefficients (*r*) from the linear regression of local JASO mean 500 hPa geopotential height onto the annual contribution of (a) the thermodynamic terms and (b) the steering terms to ln(LDI) are shown for 1900–2012. Positive values (red) are associated with anomalous high pressure, and negative values (blue) are associated with anomalous low pressure. Spatial significance exceeding a 95% confidence threshold using a Student's *t* test is outlined in green.

Both in-sample and out-of-sample LDI show significant diagnostic skill beyond all baseline methods with greater than 90% confidence (Figure 1a). In-sample and out-of-sample LDI explain 31.4% and 26.6% of hurricane landfall variability, respectively, with $P = 0.01$ and $P = 0.07$ relative to TC count using Wilcoxon signed rank tests. Figure 1b compares the annual expected rate of U.S. hurricane landfalls indicated by LDI with the observational record over 1900–2012. While LDI fluctuates between 0.46 and 4.14, compared to 0 to 6 annual U.S. hurricane landfalls, the index generally correctly sorts seasons into less active than normal, near normal, and more active than normal. Figures 1c and 1d show LDI expected landfall rates and observed U.S. hurricane landfalls for seasons in the highest and lowest 10% of LDI, respectively. The mean value of both LDI and observed hurricane landfalls in the top decile is approximately twice the climatologically expected rate of 1.73 U.S. hurricane landfalls per year, and the mean value in the bottom decile is less than half of climatology.

Each of LDI's four components is closely tied to physical processes that develop, steer, and regulate the intensity of TCs in the Atlantic basin, offering physical insight into sources of interannual variance. Since LDI is an exponential product, we examined the anomaly of each component of ln(LDI) to quantify its individual contribution to the index. We call the divergence and rSST components the "thermodynamic terms," as they are physically linked to storm-scale convective, energetic, and circulation processes [*Garner et al.*, 2009; *Zhao and Held*, 2012], and call the meridional wind and shear vorticity components linked to large-scale TC track patterns the "steering terms" [*Saunders and Lea*, 2005].

The contributions of the thermodynamic and steering groups to ln(LDI) are shown in Figure 2 to be negatively correlated ($r = -0.50$, and $P = 2.6 \times 10^{-8}$), suggesting a tension between environmental conditions conducive for development and landfall-favoring steering patterns. This negative covariance is clear from inspection of the time series in Figure 2a, particularly in recent hurricane seasons such as 2008 and 2011. Figure 2b shows TC and U.S. hurricane landfall counts averaged within the quadrants dividing positive and negative thermodynamic and steering term contributions. Moving from negative to positive steering term contribution while holding the sign of thermodynamic term contribution fixed, there is a marginal increase in quadrant-averaged TC count (less than 7%) and a much larger increase in hurricane landfall count (roughly 20–30%). This is indicative of the utility of LDI for discriminating between Atlantic hurricane seasons in which overall TC count is elevated, and seasons in which a higher proportion of developing TCs are likely to approach the continental U.S.

To physically relate the grouping of terms to global-scale climate patterns, we performed spatial correlations between the LDI contributions from the thermodynamic and steering groups with 500 hPa geopotential height anomalies (Figure 3). Positive thermodynamic contributions (Figure 3a) are linked with anomalous troughing in the western Atlantic and ridging in the subtropical eastern Atlantic, resembling the warm Atlantic Meridional Mode (AMM), associated with enhanced TC count [*Vimont and Kossin*, 2007; *Kossin and Vimont*, 2007; *Patricola et al*., 2014]. This corroborates *Colbert and Soden* [2012], in which there is a strong relationship between positive AMM and a supportive development environment for MDR TCs but no preferential relationship between AMM and MDR TC steering regimes. Positive steering contributions (Figure 3b) have a significant relationship with anomalous ridging over the eastern U.S. and a midlatitude wave train anchored by an eastern Atlantic dipole, consistent with positive NAO, associated in the literature with increased landfall potential [*Elsner et al*., 2000; *Kossin et al*., 2010]. Overall, the long-wave patterns associated with the thermodynamic and steering morphologies most favorable for U.S. landfalls are in partial opposition over much of the Northern Hemisphere, further evidence of an intrinsic tension between the two term groups of LDI. This dichotomy is one potential source of historical difficulty in understanding interannual variability in U.S. landfall activity.

5. Conclusion and Implications

Our results indicate that some means of considering TC activity in the abstract may be partially orthogonal to understanding the landfall risks TCs pose to heavily populated coastal areas. Of the modern GIs widely used to study TC activity trends in global climate models, we confirmed that most capture over half of the historical variability in Atlantic TC count in the satellite era, in agreement with the documented performance of the indices in the literature. However, none of the GIs diagnose more than 3% of the historical variability in annual U.S. hurricane landfalls. We addressed the disconnection between historical count and landfall outcomes by using a Poisson regression methodology incorporating metrics physically linked to both TC thermodynamic and steering processes to yield LDI. The overall concept of LDI as outlined in this study is objective, generalizable, and lends itself to further methodological refinements and extensions, such as application to other global basins in which TCs are a threat to life and property.

Overall, LDI successfully diagnoses a significant portion of U.S. hurricane landfall variance since 1900, reveals potential reasons why GIs do not covary with landfall count, and clarifies the physical relationship between Atlantic TC count and U.S. hurricane landfall count. As GIs have been invoked in the context of climate models unable to resolve TC-scale structures [*Royer et al*., 1998], LDI or a conceptually similar tool could serve as a proxy for changes in the number of hurricane landfalls in climate change simulations, especially since even models and downscaling efforts able to simulate TCs directly are presently unable to reliably reproduce realistic landfall statistics [*Zhao and Held*, 2012; *Knutson et al*., 2013]. Since Atlantic TC activity provides limited information about U.S. hurricane impacts, it is important that researchers take the demonstrated tension between conditions favorable for genesis and conditions favorable for landfall into account when designing studies that address direct impacts on human populations. The development of LDI is a proof of concept of the utility of diagnosing hurricane landfall risk through means other than aggregate measures of activity, in order to more accurately quantify the true societal impacts of these formidable natural hazards.

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References

Aon Benfield Impact Forecasting Group (2014), *Annual Global Climate and Catastrophe Report: Impact Forecasting—2013*, Aon Benfield, London, U.K.

Atlantic Oceanographic and Meteorological Laboratory (2016), *Continental United States Hurricane Impacts/Landfalls (1851–2015)*, Hurricane Research Division, AOML, Miami, Florida. [Available at http://www.aoml.noaa.gov/hrd/hurdat/All_U.S._Hurricanes.html.]

Bruyère, C. L., G. J. Holland, and E. Towler (2012), Investigating the use of a genesis potential index for tropical cyclones in the North Atlantic basin, *J. Clim.*, *25*, 8611–8626.

Camargo, S. J., K. Emanuel, and A. H. Sobel (2007a), Use of a genesis potential index to diagnose ENSO effects on tropical cyclone genesis, *J. Clim.*, *20*, 4819–4834.

Camargo, S. J., A. H. Sobel, A. G. Barnston, and K. Emanuel (2007b), Tropical cyclone genesis potential index in climate models, *Tellus*, *59A*, 428–443.

Camargo, S. J., M. K. Tippett, A. H. Sobel, G. A. Vecchi, and M. Zhao (2014), Testing the performance of tropical cyclone genesis indices in future climates using the HIRAM model, *J. Clim.*, *27*, 9171–9196.

Colbert, A. J., and B. J. Soden (2012), Climatological variations in North Atlantic tropical cyclone tracks, *J. Clim.*, *25*, 657–673.

Compo, G. P., et al. (2011), The twentieth century reanalysis project, *Q. J. R. Meteorol. Soc.*, *137*, 1–28.

Elsner, J. B., and C. P. Schmertmann (1994), Assessing forecast skill through cross validation, *Weather Forecast.*, *9*, 619–624.

Elsner, J. B., and T. H. Jagger (2006), Prediction models for annual U.S. hurricane counts, *J. Clim.*, *19*, 2935–2952.

Elsner, J. B., K. Liu, and B. Kocher (2000), Spatial variations in major U.S. hurricane activity: Statistics and a physical mechanism, *J. Clim.*, *13*, 2293–2305.

Emanuel, K. (2005), Increasing destructiveness of tropical cyclones over the past 30 years, *Nature*, *436*, 686–688.

Emanuel, K. (2010), Tropical cyclone activity downscaled from NOAA-CIRES reanalysis, *J. Adv. Model. Earth Syst.*, *2*, 1908–1958, doi:10.3894/JAMES.2010.2.1.

Emanuel, K. (2011), Global warming effects on U.S. hurricane damage, *Weather Clim. Soc.*, *3*, 261–268.

Emanuel, K., F. Fondriest, and J. P. Kossin (2012), Potential economic value of seasonal hurricane forecasts, *Weather Clim. Soc.*, *4*, 110–117.

Enfield, D. B., A. M. Mestas-Nunez, and P. J. Trimble (2001), The Atlantic multidecadal oscillation and its relation to rainfall and river flows in the continental U.S, *Geophys. Res. Lett.*, *28*, 2077–2080, doi:10.1029/2000GL012745.

Garner, S. T., I. M. Held, T. R. Knutson, and J. Sirutis (2009), The role of wind shear and thermal stratification in past and projected changes of Atlantic tropical cyclone activity, *J. Clim.*, *22*, 4723–4734.

Goldenberg, S. B., C. W. Landsea, A. M. Mestad-Nuñez, and W. M. Gray (2001), The recent increase in Atlantic hurricane activity: Causes and implications, *Science*, *293*, 474–479.

Gray, W. M. (1979), Hurricanes: Their formation, structure and likely role in the tropical circulation, in *Meteorology Over Tropical Oceans*, edited by D. B. Shaw, pp. 155–218, Royal Meteorological Society, Berkshire.

Jones, P. D., T. Jonsson, and D. Wheeler (1997), Extension to the North Atlantic Oscillation using early instrumental pressure observations from Gibraltar and south-west Iceland, *Int. J. Climatol.*, *17*, 1433–1450.

Kerr, R. A. (2000), A North Atlantic climate pacemaker for the centuries, *Science*, *288*, 1984–1985.

Knapp, K. R., M. C. Kruk, D. H. Levinson, H. J. Diamond, and C. J. Neumann (2010), The international best track archive for climate stewardship (IBTrACS), *Bull. Am. Meteorol. Soc.*, *91*, 363–376.

Knutson, T. R., J. J. Sirutis, G. A. Vecchi, S. Garner, M. Zhao, H.-S. Kim, M. Bender, R. E. Tuleya, I. M. Held, and G. Villarini (2013), Dynamical downscaling projections of 21st century Atlantic hurricane activity: CMIP3 and CMIP5 Twentieth Century simulations, *J. Clim.*, *26*, 6591–6617.

Kossin, J. P., and D. J. Vimont (2007), A more general framework for understanding Atlantic hurricane variability and trends, *Bull. Am. Meteorol. Soc.*, *88*, 1767–1781.

Kossin, J. P., S. J. Camargo, and M. Sitkowski (2010), Climate modulation of North Atlantic hurricane tracks, *J. Clim.*, *23*, 3057–3076.

Landsea, C. W., and J. L. Franklin (2013), Atlantic hurricane database uncertainty and presentation of a new database format, *Mon. Weather Rev.*, *141*, 3576–3592.

Landsea, C. W., R. A. Pielke, A. M. Mestas-Nuñez, and J. A. Knaff (1999), Atlantic basin hurricanes: Indices of climatic changes, *Clim. Change*, *42*, 89–129.

Landsea, C. W., G. A. Vecchi, L. Bengtsson, and T. R. Knutson (2010), Impact of duration thresholds on Atlantic tropical cyclone counts, *J. Clim.*, *23*, 2508–2519.

Lehmiller, G. S., T. B. Kimberlain, and J. B. Elsner (1997), Seasonal prediction models for North Atlantic basin hurricane location, *Mon. Weather Rev.*, *125*, 1780–1791.

McGauley, M. G., and D. S. Nolan (2011), Measuring environmental favorability for tropical cyclogenesis by statistical analysis of threshold parameters, *J. Clim.*, *24*, 5968–5997.

Menkes, C. E., M. Lengaigne, P. Marchesiello, N. C. Jourdain, E. M. Vincent, J. Lefèvre, F. Chauvin, and J.-F. Royer (2012), Comparison of tropical cyclogenesis indices on seasonal to interannual timescales, *Clim. Dyn.*, *38*, 301–321.

Patricola, C. M., R. Saravanan, and P. Chang (2014), The impact of the El Niño–Southern Oscillation and Atlantic Meridional Modes on seasonal Atlantic tropical cyclone activity, *J. Clim.*, *27*, 5311–5328.

Royer, J. F., F. Chauvin, B. Timbal, P. Araspin, and D. Grimal (1998), A GCM study of the impact of greenhouse gas increase on the frequency of occurrence of tropical cyclones, *Clim. Change*, *28*, 307–353.

Ryan, B. F., I. G. Watterson, and J. L. Evans (1992), Tropical cyclone frequencies inferred from Gray's yearly genesis parameter: Validation of GCM tropical climates, *Geophys. Res. Lett.*, *19*, 1831–1834, doi:10.1029/92GL02149.

Saunders, M. A., and A. S. Lea (2005), Seasonal prediction of hurricane activity reaching the coast of the United States, *Nature*, *434*, 1005–1008.

Smith, T. M., R. Reynolds, T. Peterson, and J. Lawrimore (2008), Improvements to NOAA's historical merged land-ocean surface temperature analysis (1880–2006), *J. Clim.*, *21*, 2283–2296.

Tippett, M. K., S. J. Camargo, and A. H. Sobel (2011), A Poisson regression index for tropical cyclone genesis and the role of large-scale vorticity in genesis, *J. Clim.*, *24*, 2335–2357.

Tolwinski-Ward, S. E. (2015), Uncertainty quantification for a climatology of the frequency and spatial distribution of North Atlantic tropical cyclone landfalls, *J. Adv. Model. Earth Syst.*, *7*, 305–319, doi:10.1002/2014MS000407.

Truchelut, R. E., and R. E. Hart (2011), Quantifying the possible existence of undocumented Atlantic warm-core cyclones in NOAA/CIRES 20th Century Reanalysis data, *Geophys. Res. Lett.*, *38*, L08811, doi:10.1029/2011GL046756.

Truchelut, R. E., R. E. Hart, and B. Luthman (2013), Global identification of previously undetected pre-satellite-era tropical cyclone candidates in NOAA/CIRES twentieth-century reanalysis data, *J. Appl. Meteorol. Climatol.*, *52*(10), 2243–2259.

Vecchi, G. A., and B. J. Soden (2007), Effect of remote sea surface temperature change on tropical cyclone potential intensity, *Nature*, *450*, 1066–1070.

Vecchi, G. A., and T. R. Knutson (2011), Estimating annual numbers of Atlantic hurricanes missing from the HURDAT database (1878–1965) using ship track density, *J. Clim.*, *24*, 1736–1746.

Villarini, G., G. A. Vecchi, T. R. Knutson, and J. A. Smith (2011), Is the recorded increase in short duration North Atlantic tropical storms spurious? *J. Geophys. Res.*, *116*, D110114, doi:10.1029/2010JD015493.

Vimont, D. J., and J. P. Kossin (2007), The Atlantic meridional mode and hurricane activity, *Geophys. Res. Lett.*, *34*, L07709, doi:10.1029/2007GL029683.

Wilcoxon, F. (1945), Individual comparisons by ranking method, *Biom. Bull.*, *1*, 80–83.

Wilks, D. S. (2006), On "field significance" and the false discovery rate, *J. Appl. Meteorol.*, *45*, 1181–1189.

Wolter, K., and M. S. Timlin (2011), El Niño/Southern Oscillation behavior since 1871 as diagnosed in an extended multivariate ENSO index (MEI.ext), *Int. J. Climatol.*, *31*, 1074–1087.

Zhao, M., and I. M. Held (2012), TC-permitting GCM simulations of hurricane frequency response to sea surface temperature anomalies projected for the late-twenty-first century, *J. Clim.*, *25*, 2995–3009.