As the Wind Blows? Understanding Hurricane Damages at the Local Level through a Case Study Analysis

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ABSTRACT

An understanding of the potential drivers of local-scale hurricane losses is developed through a case study analysis. Two recent category-3 U.S. landfalling hurricanes (Ivan in 2004 and Dennis in 2005) are analyzed that, although similar in terms of maximum wind speed at their proximate coastal landfall locations, caused vastly different loss amounts. In contrast to existing studies that assess loss mostly at the relatively aggregate level, detailed local factors related to hazard, exposure, and vulnerability are identified. State-level raw wind insured loss data split by personal, commercial, and auto business lines are downscaled to the census tract level using the wind field. At this scale, losses are found to extend far inland and across business lines. Storm size is found to play an important role in explaining the different loss amounts by controlling not only the size of the impacted area but also the duration of damaging winds and the likelihood of large changes in wind direction. An empirical analysis of census tract losses provides further evidence for the importance of wind duration and wind directional change in addition to wind speed. The importance of exposure values however is more sensitive to assumptions in how loss data are downscaled. Appropriate consideration of these local drivers of hurricane loss may improve historical loss assessments and may also act upscale to impact future projections of hurricane losses under climate and socioeconomic change.

1. Introduction

Much of the existing hurricane loss research is focused at a relatively aggregate scale over many storms where maximum wind speed at landfall (raised between the third and ninth power) is found to explain the largest variance in loss (Mendelsohn et al. 2012; Murphy and Strobl 2010; Nordhaus 2006, 2010; Schmidt et al. 2009, 2010).[1] However, it is quite plausible that other physical wind field characteristics, such as duration of hurricane force winds, as well as relevant exposure and vulnerability factors, emerge as important local-level contributions to loss, thereby reducing the role of maximum wind speed at the relatively local scale (Nordhaus 2006, 2010). Certainly, the three most recent U.S. landfalling hurricanes (Irene, Isaac, and Sandy) have shown that losses from low intensity storms can be significant,[2] even hundreds of miles away from landfall location. As hurricane losses are often best mitigated from a local perspective, it is therefore important to delineate other potential factors in addition to maximum wind speed at landfall driving hurricane losses at the relatively local level (Kantha 2006; Neumayer and Barthel 2011).[3]

[1] Murnane and Elsner (2012) found an exponential relationship between maximum wind speed and loss is a better fit than a power law.

[2] Irene total damages at approximately \$15.8 billion place it in the top 10 costliest hurricanes on record through 2011 (http://www.wunderground.com/hurricane/damage.asp?MR=1), and loss estimates for Sandy of approximately \$65.7 billion (http://www.ncdc.noaa.gov/billions/events) place it second behind Katrina in 2005.

[3] Smith and Katz (2013) point out the need for local-scale analysis to avoid potential bias in loss estimation.

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Of course, some aggregate-level hurricane loss studies have investigated analogs of wind speed such as minimum pressure (Malmstadt et al. 2009; Mendelsohn et al. 2012; Nordhaus 2006, 2010) and other physical characteristics of the hurricane such as translational speed and duration of winds (Chavas et al. 2012; Murphy and Strobl 2010; Nordhaus 2006, 2010; Strobl 2011). Holland et al. (2010) showed that wind speed is only a minor contributor to offshore energy industry losses compared to hurricane size and translation speed, but it is likely that drivers of losses will differ between offshore and onshore locations. At the local level Powell et al. (1995, p. 501) suggests that wind duration is relevant to damage because of "repeated loading and unloading caused by cycles of gusts and lulls in a turbulent wind field" and for a case study of Hurricane Andrew (1992) they found that the duration of hurricane force (>33 m s^{-1}) sustained winds show exponential relationship to loss above a threshold of 1 h. Jain (2010) concludes a similar finding of the importance of duration especially at low to moderate wind speeds. Powell et al. (1995) also found a negative relationship between loss and wind steadiness defined as the ratio of the vector wind to the wind speed over the lifetime of the storm (i.e., a measure of the directional uniformity of the winds). Despite the inclusion of these other wind speed characteristics in the literature, maximum wind speed at landfall is still the dominant physical factor utilized in loss modeling (Jain 2010).

Furthermore, few studies attempt to link the physical hurricane characteristics to detailed loss, exposure, and vulnerability data, thereby exploring jointly their relative importance at the local scale. Existing studies often take normalized loss data and assume losses are confined to specified affected and/or coastal counties[4] to explore relationships to landfall maximum wind speed (Mendelsohn et al. 2012; Nordhaus 2006, 2010; Pielke et al. 2008; Sadowski and Sutter 2005). Despite these limitations, Jagger et al. (2011) are able to detect climate signals in the Pielke et al. (2008) dataset that are consistent with the physical understanding about hurricanes and climate, suggesting that at the aggregate level these assumptions are reasonable. Overall then, as Bouwer (2011, p. 40) states, "...the complex interaction between hazards, exposure, and vulnerability has so far not been approached in a uniform manner through impact studies that would allow inclusion in economic models and cost–benefit analyses."

In this study, we therefore conduct a detailed assignment (rather than relying on normalization techniques) and empirical assessment of hurricane loss, hazard, exposure, and vulnerability data to increase understanding of the potential drivers of loss at the local scale. We focus on a case study analysis contrasting two recent U.S. landfalling hurricanes that, although similar in terms of maximum wind speed at their proximate coastal landfall locations, caused vastly different losses. Hurricane Ivan made U.S. landfall in Gulf Shores, Alabama, as a category-3 hurricane (54 m s^{-1} maximum winds) on 16 September 2004. Nearly a year later, on 10 July 2005, category-3 Hurricane Dennis (54–56 m s^{-1} maximum winds) made landfall approximately 30 miles to the east at Santa Rosa Island, Florida. Hurricane Ivan losses (insured and uninsured) are estimated to be approximately \$14.2 billion while Hurricane Dennis losses are estimated to be approximately \$2.2 billion or nearly 6½ times less than Ivan (http://www.icatdamageestimator.com/). Clearly, maximum wind speed at landfall alone does not explain the loss difference between these two events. In contrasting these two storms, we provide evidence for other potential factors in addition to maximum wind speed in driving hurricane losses at the relatively local level.

Section 2 presents an overview of Ivan and Dennis using raw loss data. Section 3 describes the impacted geographic area using swaths of maximum winds. Section 4a explores characteristics of the wind field and their spatial variability across the impacted area, whereas section 4b explores characteristics of exposure and vulnerability. Hazard, exposure, vulnerability components are then analyzed in combination in section 5 to explore their relative contributions to loss. A summary discussion concludes the paper in section 6.

2. Loss data overview

Loss datasets are notoriously inconsistent (Guha-Sapir and Below 2002; Gall et al. 2009; Bouwer 2011; Kron et al. 2012; Pendleton et al. 2013). Direct losses range from \$7.0 billion to \$18.8 billion (269% difference) for Ivan and from \$1.7 billion to \$2.5 billion (147% difference) for Dennis (Table 1). It is an open question as to the magnitude of flood losses in these loss estimates,[5] but Table 1 illustrates this is likely more of an issue for Hurricane Ivan given the \$1.7 billion in flood losses from the National Flood Insurance Program (NFIP) database.

[4] The National Hurricane Center lists county-by-county hurricane strikes (direct and indirect) from each hurricane from 1900 to 2009 (http://www.aoml.noaa.gov/hrd/hurdat/Data_Storm.html). Strikes are constrained to the 175 counties listed, of which 168 (96%) are coastal counties: that is, some portion of their county boundary directly abuts the Atlantic Ocean, an associated inlet, or the Gulf of Mexico.

[5] The National Hurricane Center (NHC) deadliest and costliest (Blake et al. 2007) includes adjusted NFIP flood damage amounts.

TABLE 1. Total loss estimates for Hurricanes Ivan and Dennis from a number of sources in nonadjusted dollars (Blake et al. 2007; http://www.emdat.be/; http://www.icatdamageestimator.com/; SHELDUS 2012).

Loss estimates	Dennis (2005)	Ivan (2004)
National Hurricane Center deadliest and costliest	$2,545,000,000	$18,820,000,000
EM-DAT	$2,230,000,000	$18,000,000,000
EM-DAT insured	$1,115,000,000	$12,000,000,000
ICAT damage estimator	$2,230,000,000	$14,200,000,000
Spatial Hazard Events and Losses Database for the U.S. (SHELDUS)	$1,732,948,980	$6,955,992,416
NFIP	$119,805,748	$1,714,317,295

Further, loss estimates may include insured losses, uninsured losses, or a mix of both. Insured losses are generally more accurately reported and often a doubling of losses is used to estimate total (the sum of insured and uninsured) losses (Pielke et al. 2008). The Emergency Events Database (EM-DAT) is the only source that provides a separate estimate of insured losses only, and for Dennis this is double the insured loss but for Ivan this is not the case (Table 1).

Access to the more detailed Property Claim Services (PCS) loss database (ISO 2013) allows us to explore spatial loss for Ivan and Dennis and develop an understanding of the large differences in total loss. PCS, an insurance industry statistical agent, estimates the insured losses by directly surveying insurance companies about their claims after major events. It is the primary source for insured losses in the United States and estimates are typically based on 40% of total claims data. PCS loss data are revised over time and here we use the final revised estimates: 19 October 2005 for Ivan and 22 November 2005 for Dennis. These data are at the state level split by type of insured loss: commercial, personal, and auto. A 95%–97% market share for personal and commercial losses is assumed by PCS, while a 50% market share is assumed for auto. Each estimate reflects PCS's "best judgment of the total insured payment for personal and commercial property lines of insurance covering fixed property, personal property, time element losses, vehicles, boats, and related property items." Their estimates do not include "loss involving uninsured property, including uninsured publicly owned property and utilities, agriculture, aircraft, and property insured under the National Flood Insurance Program (NFIP)" PCS (2012, personal communication). Thus, these data include all wind related losses—hurricane, tornado, etc.—but exclude any significant flood losses.

PCS insured losses spread far inland beyond the landfall states of Alabama for Ivan and Florida for Dennis (Fig. 1a) with nonnegligible losses outside the two states of closest proximity to landfall: 15% of total loss for Ivan and 13% for Dennis. Moreover, it is certainly possible that losses occurred outside of coastal regions within the landfall states. This has important implications to existing hurricane damage loss modeling and normalization studies where it is typically assumed that damages stem from affected and/or coastal counties, limited to the landfall states (e.g., Mendelsohn et al. 2012; Pielke et al. 2008).[6]

Further, losses are not concentrated in one business line. For Ivan, total losses are 72% personal, 24% commercial, and 4% auto, while for Dennis total losses are 63% personal, 30% commercial, and 7% auto. Additionally, this division of losses across business lines is not consistent across storms. State personal line losses, for example, range from 20% to 85% of total loss (Fig. 1b and Table 2). Varying business line losses also have important implications to existing hurricane damage loss modeling and normalization studies where 1) no clear distinction is made between business line losses or 2) accounting for losses over time and/or in the loss estimation is commonly done using personal business line type proxies. For example, the Pielke et al. (2008) normalization uses the relationship between population and housing unit growth over time in the impacted counties, not commercial enterprise growth in those counties.[7] It is questionable whether commercial enterprises would grow at the same rate or in the same proportions as the growth in population and housing units. For example, in Santa Rosa County, Florida, where Hurricane Dennis made landfall in 2005, population grew at a slightly positive rate from 2005 to 2006, whereas square footage of commercial construction declined by 19% (Haas Center 2008). More broadly in Santa Rosa County over the period from 2000 to 2011, population grew by 30%, whereas from 2000 to 2010 total employment increased by only 24%: a 36% increase in service sector industries but a 9% decrease in nonservice sector related industries (Headwaters Economics 2012).

[6] Hurricanes can affect the weather far outside the region of hurricane force winds resulting in other wind-associated damaging weather such as severe thunderstorms and tornadoes hundreds of kilometers from the hurricane track. Hurricane Ivan in particular was a prolific producer of tornadoes with 117 reported across eight states from the Gulf Coast to Pennsylvania. It is likely the losses in states that did not experience hurricane force winds can be partly attributed to these hurricane spawned tornadoes.

[7] The Pielke et al. normalized data are adjusted for wealth increases which are defined as "current-cost net stock of fixed assets and consumer durable goods" (Pielke et al. 2008, p. 9). However, this adjustment is done at a national level, not necessarily specific to the impacted areas. Further, fixed assets are defined more broadly than just commercial fixed assets including private residential fixed assets as well as all types of government fixed assets.

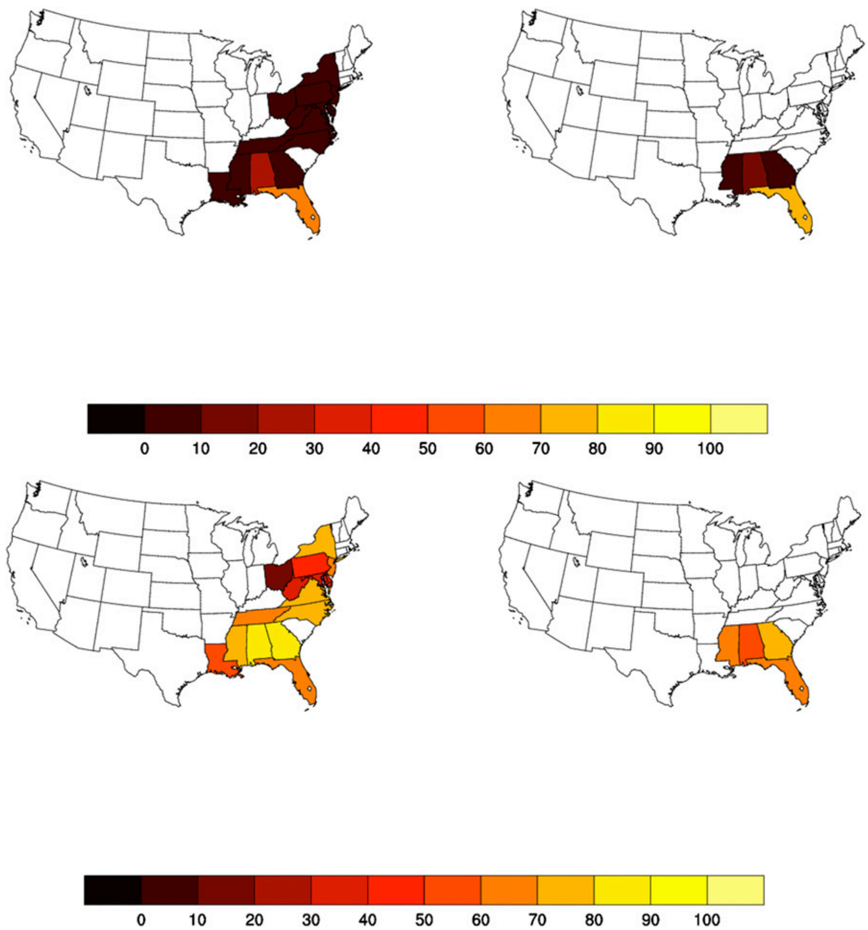

FIG. 1. (a) PCS state losses as a percent of storm total loss for (left) Ivan and (right) Dennis. (b) PCS state personal business line losses as a fraction of total state loss for (left) Ivan and (right) Dennis.

Table 2 shows state-by-state hurricane Ivan loss data combined with mean maximum wind speed data.[8] At the state-level loss does not increase monotonically with maximum wind speed. For example, while Louisiana is ranked 12th in total Ivan state losses (0.2% of total), the mean sustained wind in Louisiana is higher than in both Georgia and Mississippi, 3rd and 6th in losses, respectively. Clearly, factors other than wind speed are contributing to variations in state-level losses, and these are explored first by defining the impacted geographical area on a substate level in the next section.

3. Defining the impacted area

Hazard, exposure, and vulnerability vary considerably on scales smaller than the spatial scale of the state-level loss data. To determine the impacted exposure and vulnerability at a reasonable level of spatial granularity, it therefore becomes necessary to determine the hazard impacted geographical areas on a substate level. Since PCS loss data are mainly attributed to wind damage, we choose here to define impacted geographical areas for Ivan and Dennis in terms of attributes of the hurricane wind field (following Murphy and Strobl 2010; Strobl 2011; Schmidt et al. 2009, 2010). The wind engineering literature contains many examples of damage functions using wind speed (e.g., Huang et al. 2001; Pinelli et al. 2004). These indicate significant damage starts to occur for wind speeds greater than hurricane force ($33\,\mathrm{m\,s^{-1}}$). It seems reasonable then to define impacted areas using the swath of maximum wind speeds above hurricane force. However hurricane winds at the land surface are highly turbulent because of interaction with the high friction land surface and damaging 3-s gusts can far exceed the mean wind speed (Vickery et al. 2009). To explore sensitivity to the threshold wind speed, we define three physically based wind speed thresholds:

[8] Wind speed data are described in the next section.

TABLE 2. Hurricane Ivan view of combined state loss and wind speed data.

Hurricane Ivan impact by state	Percentage of total Ivan loss	Percentage of state loss by personal business line	Number of census tracts with sustained winds > 0	Mean of sustained wind ($m\,s^{-1}$)
Florida	60%	67%	164	30.0
Alabama	25%	85%	570	24.2
Georgia	5%	83%	1	14.6
Pennsylvania	3%	49%	—	—
North Carolina	2%	74%	—	—
Mississippi	1%	76%	346	17.7
Virginia	1%	77%	—	—
Tennessee	1%	67%	—	—
Maryland	0.4%	33%	—	—
New York	0.3%	75%	—	—
West Virginia	0.3%	40%	—	—
Louisiana	0.2%	60%	388	18.6
New Jersey	0.2%	67%	—	—
Ohio	0.2%	20%	—	—
Delaware	0.1%	40%	—	—
Total	100%	72%	1469	22

hurricane force ($33\,m\,s^{-1}$) 1-min mean wind, a slightly reduced 1-min mean wind speed that can sustain 3-s hurricane force gusts ($25\,m\,s^{-1}$; using a gust factor of 1.3 following Vickery et al. 2009), and tropical storm force ($17\,m\,s^{-1}$) 1-min mean wind.

Gridded observed surface wind swath data are available from the National Oceanic and Atmospheric Administration (NOAA) Hurricane Research Division (HRD) Real-time Hurricane Wind Analysis System (H*Wind) project (Powell et al. 1998). H*Wind analyses are based on available surface, aircraft, and remote sensing data and represent a readily accessible, publically available surface wind analysis for historical hurricanes. H*Wind data are interpolated to the census tract level in GIS, taking the mean of all H*Wind values that intersect each census tract.[9] We then select census tracts with mean maximum wind speed (designated here as the census tract sustained wind speed value) > 0 to form our general impacted geographic area. Finally, we define three sets of impacted census tracts according to the three wind speed thresholds.

Ivan impacted a much larger area than Dennis for all three wind speed thresholds (Figs. 2a,b and Table 3). Ivan's hurricane force winds impacted nearly 5300 square miles compared to approximately 1000 square miles for Dennis. Overall, Ivan impacted 11, 4, and 6 times as many census tracts as compared to Dennis in terms of hurricane force, hurricane gust, and tropical storm strength winds. Assuming that the swath of winds defines the impacted region, the likely first order reason for the difference in losses between Ivan and Dennis then is the difference in size of the impacted area (rather than storm maximum wind speed). Storm size not only affects the number of impacted tracts but also has direct influence on other attributes of the wind field: storm size controls wind duration by determining the time taken for damaging winds to transit a point location for a given translation speed and also controls the number of tracts experiencing a high degree of directional change of the mean wind.

For both storms, hurricane force and hurricane gust impacted areas were concentrated into specific counties of each impacted state, and not all impacted counties are coastal. For example, Dennis (Fig. 3) impacted two states, Florida and Alabama, and two counties in each of these two states, Escambia and Santa Rosa Counties in Florida and Escambia and Monroe Counties in Alabama, which are both inland Alabama counties.[10] Furthermore, impacts are specific to particular portions of each impacted county (as shown for Dennis in Fig. 3). Indeed, in Monroe County, Alabama, and Escambia County, Florida, hurricane force winds only impacted 14% and 8% of county areas, respectively.

This local analysis has important implications to existing hurricane damage loss modeling and normalization studies where often only affected and/or coastal landfall counties are analyzed, or losses are assumed to occur in the entire county with associated explanatory variables following suit such as population or income.

[9] Since we are joining the H*Wind data at the relatively granular census tract level, it is necessary to regrid the gridded H*Wind data to ensure no spatial gaps exist in the gridded data at this geographic level. We also incorporated nearest values of wind speed within 1-mile distance to ensure no data gaps with the regridded data.

[10] Nor do these counties appear in the NHC affected county list.

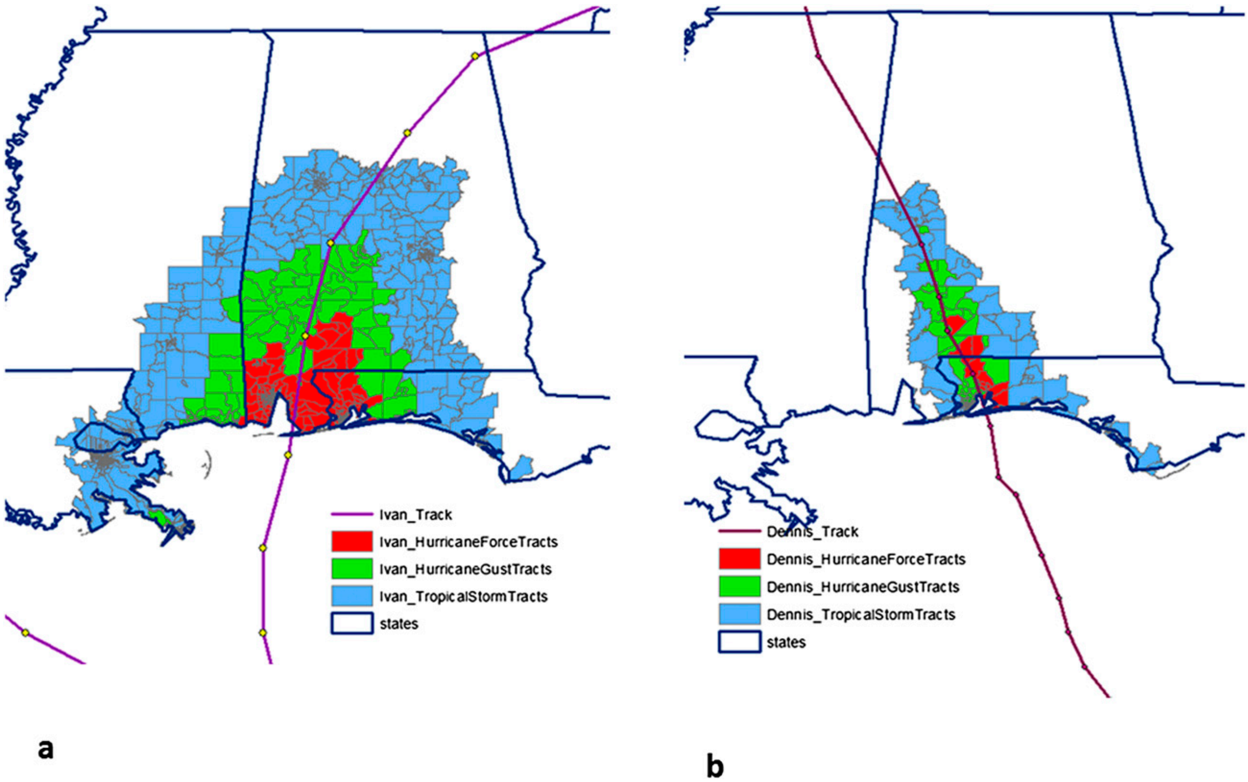

FIG. 2. (a) Hurricane Ivan impacted geographical areas. (b) Hurricane Dennis impacted geographical areas.

Mendelsohn et al. (2012), for example, "… empirically test the importance of local income and population. Income and population were based on the five coastal counties near where the eye of the storm strikes land." (Mendelsohn et al. 2012, p. 10). For Dennis, this would not be an appropriate strategy as the true local income and population data would be misrepresented from an aggregate county perspective. For example, the five Escambia County, Florida, census tracts experiencing hurricane force winds (Fig. 3) represent only 6% of the county population and 8% of the county housing units. Additionally, the local population of the noncoastal counties experiencing hurricane force winds would not be represented at all. This may have contributed to the authors finding that "the vulnerability variables (income and population density) are not significant in Table 1, which poses a dilemma for the analysis." (Mendelsohn et al. 2012, p. 11).

4. Hazard and exposure/vulnerability characteristics in the impacted area

Given the state-level loss data broken down by business line and our defined impacted areas, we can systematically begin to understand the nature of the relationship between loss and hazard, exposure, and vulnerability characteristics. To provide focus, we describe only personal line losses for census tracts impacted by

TABLE 3. Ivan and Dennis defined impacted geographical area summary.

Impacted area criteria	No. of impacted census tracts: Ivan (2004)	No. of impacted census tracts: Dennis (2005)	Total square miles: Ivan (2004)	Total square miles: Dennis (2005)	Ivan impacted census tract sustained wind speeds ($m\,s^{-1}$): Min	Mean	Max	Dennis impacted census tract sustained wind speeds ($m\,s^{-1}$): Min	Mean	Max
Hurricane force ($\geq 33\,m\,s^{-1}$)	228	21	5292	1048	33	37	42	33	37	44
Hurricane gust (factor of 1.3; $\geq 25\,m\,s^{-1}$)	382	98	17 031	3760	25	33	42	25	31	44
Tropical storm ($\geq 17\,m\,s^{-1}$)	1112	202	46 659	12 189	17	24	42	17	26	44

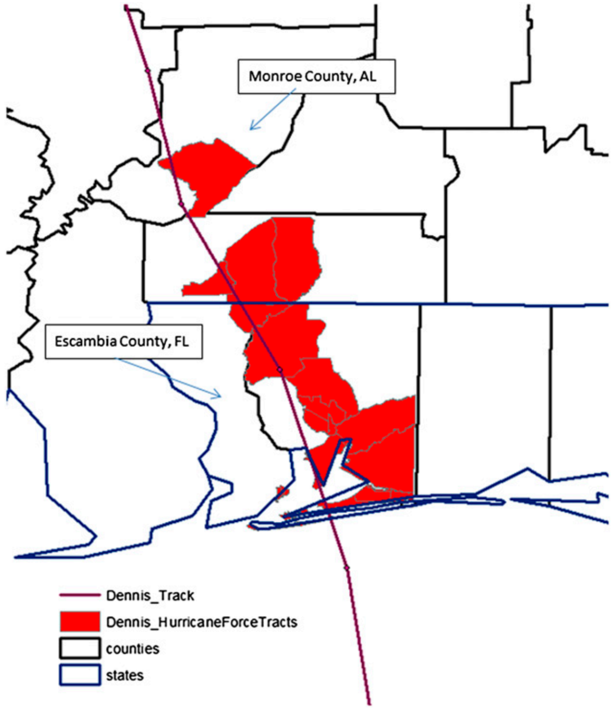

FIG. 3. Hurricane Dennis hurricane force census tracts by county and state.

hurricane force winds, in terms of exposure, vulnerability, and wind field attributes.

a. Wind field characteristics in the impacted area

After accounting for the difference in area of winds, the distributions of census tract average wind field attributes of speed, duration, and directional uniformity are also different between Ivan and Dennis. While mean sustained wind speeds are the same across both storms at $37\,\mathrm{m\,s^{-1}}$, the distributions of census tract average values are quite different. Ivan has heavier weighting to category-1 status ($< 42\,\mathrm{m\,s^{-1}}$)[11] with 26% of the total tracts between 38 and $40\,\mathrm{m\,s^{-1}}$ (Fig. 4a), while for Dennis the corresponding portion of tracts is 14% and the distribution for Dennis has a longer tail. The distributions of census tract average hurricane force wind duration (Fig. 4b) are also markedly different between Ivan and Dennis, with no values above 1 h for Dennis but approximately 90% of values above 1 h for Ivan and a tail extending beyond 4 h. The distributions of directional uniformity (Fig. 4c, where values of 1 indicate no change in wind direction over the lifetime of the storm and values of 0 indicate wind experienced equally from all directions) are also different between the storms with Ivan showing a broader range of values than Dennis, an expected result of the larger size of Ivan than Dennis.

The different distributions are due to both differences in the storm size and differences in the geographies of the affected census tracts since the high census tract densities in urban areas act to weight the values in these regions more than in rural areas characterized by low-density census tracts. The interaction between the spatially varying wind swath and spatially varying census tract density creates a situation in which the distributions of tract average hazard variables are extremely sensitive to the hurricane track. Thus, it is important to not only properly account for the impacted area but also account for the inherent spatial variability within.

b. Exposure, vulnerability, and losses in the impacted area

Differences in exposure and vulnerability within the impacted areas are potentially important for loss characterization (Bouwer 2011). For example, as RMS (2008, p. 12) states in regard to the quality of exposure data used in catastrophe modeling, "Modeled results are only as robust as the exposure data entered into them. In fact, when missing or incorrect information is enhanced, it is not uncommon to see loss estimates change by a factor of four on a single building." Here we detail differences in exposure and vulnerability between the Ivan and Dennis hurricane force wind impacted census tracts in terms of the amount, composition, and value of building property exposure; the age of the housing units; and demographic information often associated with a household's ability to self-protect from a storm and thus reduce damages.[12]

For Ivan, 228 hurricane force wind impacted tracts covered 5292 square miles, 1.036 million people (1730 people per square mile), and \$46.9 billion in total residential building value with the majority classified as single-family dwellings (74%) as shown in Table 4. Comparatively, the 21 hurricane force wind impacted tracts for Dennis covered 1048 square miles, 125 123 people (719 people per square mile), and \$5.5 billion in total residential

[11] Although both storms are classified as category-3 hurricanes at landfall, sustained hurricane force wind values in the impacted census tracts are well below this amount and are a consequence of both area averaging and the abrupt reduction of wind speeds at the coast in the H*Wind analysis.

[12] Exposure and vulnerability data are sourced from HAZUS-Multi-Hazard (MH) 2.1. Their general building stock data are sourced from year 2000 U.S. Census Bureau data and year 2002 Dun and Bradstreet data, prior to the occurrence of both Ivan and Dennis (http://www.fema.gov/media-library-data/20130726-1820-25045-8522/hzmh2_1_hr_um.pdf).

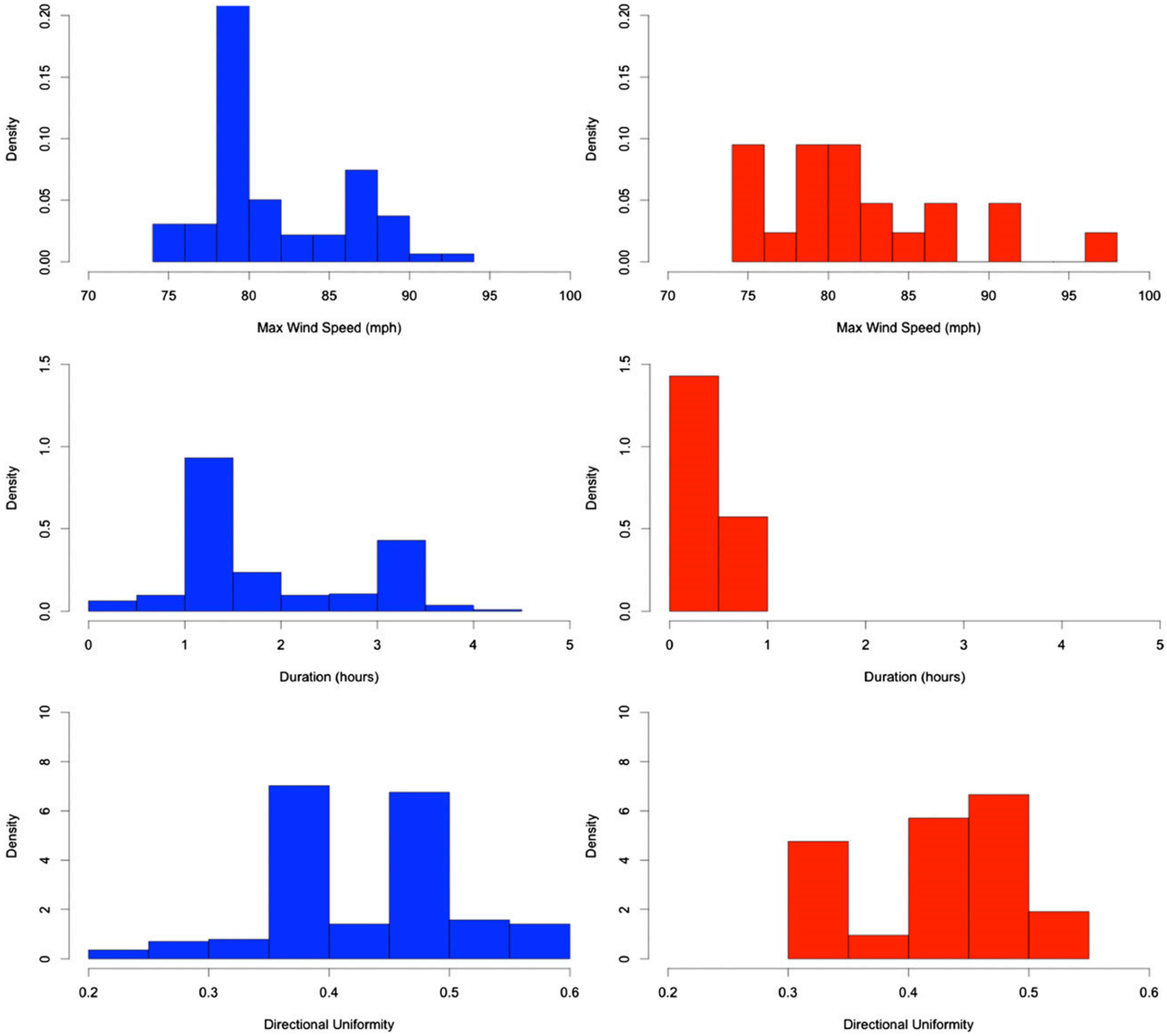

FIG. 4. Distribution of census tract average (a) maximum wind speeds, (b) duration of hurricane force winds, and (c) directional uniformity for census tracts impacted by Ivan's hurricane force winds (data source: H*Wind; Powell et al. 1998).

building value again with the majority classified as single-family dwellings (68%). Thus, while Ivan impacted 5 times the area and 11 times as many census tracts, it impacted 8.2 times as many people (but only 2.4 times as many people per square mile), 7.5 times the number of total residential structures, and 8.5 times the replacement cost dollar-valued residential building exposure. Given that total losses are reported to be 6.4 times as large for Ivan as they are for Dennis, clearly variations in size and exposure in the impacted areas affect the end loss results in nonlinear and complex ways that should be addressed in loss estimations (Bouwer 2011).

A further breakdown of the exposed residential value data by building type shows that the impacted average building replacement costs were generally higher in Ivan (Fig. 5). Thus, not only did Ivan impact 7.5 times as many residential structures, but on average each of these impacted residential structures has a higher building replacement cost at $113,716 compared to $99,992 for Dennis. All else being equal then, losses for a hurricane impacting the Ivan hurricane force census tracts should be higher on average than a similar hurricane impacting the Dennis hurricane force census tracts simply because of the differences in average building replacement cost value.

However, the breakdown of hurricane force impacted residential structures by building type is also different between Ivan and Dennis. For example, in Ivan's Alabama hurricane force impacted tracts, 74% of the residential structures in these tracts are classified as

TABLE 4. Ivan and Dennis hurricane force impacted tracts exposure summary.

	No. of Structures Impacted		Total Value of Exposure	
Residential exposure type	Ivan: Alabama, Florida, and Mississippi	Dennis: Alabama and Florida	Ivan: Alabama, Florida, and Mississippi	Dennis: Alabama and Florida
Single family	307 446	37 368	$36,853,249,000	$4,455,684,000
Manufactured housing	52 446	8706	$1,974,634,000	$328,529,000
Duplex: 1–2 units	13 331	2392	$954,822,000	$109,472,000
Duplex: 3–4 units	12 286	2017	$753,147,000	$78,048,000
Duplex: 5–9 units	9170	1773	$1,397,874,000	$116,799,000
Duplex: 10–19 units	6091	1088	$693,166,000	$56,749,000
Duplex: 20–49 units	5371	901	$549,683,000	$68,251,000
Duplex: more than 50 units	5323	749	$1,163,592,000	$119,737,000
Temporary lodging	311	38	$450,584,000	$60,845,000
Institutional dormitories	788	40	$1,922,013,000	$96,731,000
Nursing homes	155	14	$219,905,000	$17,336,000
Total	412 718	55 086	$46,932,669,000	$5,508,181,000

single-family dwellings, compared to 58% for Dennis. Conversely, 42% of the Alabama impacted residential structures for Dennis are either manufactured housing or duplex structure, almost double the 26% for Ivan. Further, the Alabama average manufactured housing building exposure values are 3.2 times less than the average single-family dwelling values ($119,238 versus $37,736), while the Alabama average duplex values across all duplex types are 1.6 times less than the average single-family dwelling values ($119,238 versus $73,018). Thus, combining the average building values with the building structure mix in the hurricane force impacted census tracts likely helps to explain the result shown in Fig. 1b that personal property losses are 85% of Ivan's total Alabama losses but only 57% of Dennis's total Alabama losses.

A potentially important vulnerability factor is residential building age. Dennis impacted a larger percentage of housing units built after 1990 (32%) as compared to Ivan (23%).[13] This is likely a factor in reducing resulting damage in Dennis as more newly constructed homes have to adhere to stronger hurricane related building codes that have been implemented since Hurricane Andrew in 1992, certainly in Florida. Finally, from a demographic perspective homeowners as compared to renters are thought to have more interest in protecting one's own property as well as being more informed about what to do for such an event. Ivan impacted tracts had a larger percentage of renter occupied households (25%) as compared Dennis impacted tracts (20%), potentially another contributing factor toward higher overall storm losses.

[13] While it is certainly plausible to think that some of this larger percentage for Dennis is due to the homes destroyed by Ivan and thus newly constructed for Dennis, it is not likely much of a contributing factor because the source of these data is ascribed to Dun and Bradstreet (2002) data.

5. Relative importance of hazard and exposure/vulnerability factors to census tract-level losses

Motivated by Powell et al. (1995), who suggest a key role for other wind field attributes in addition to wind speed in driving losses at the local scale, we now explore duration and directional change as alternatives to wind speed in explaining tract-level variations in personal losses accounting for exposure. In contrast to wind speed, the state totals of tract average duration of hurricane force winds and directional uniformity do indeed increase monotonically with average personal business line loss (Table 5). For example, in the 149 impacted hurricane force census tracts in Alabama the average personal business line loss is $10,495 per $200,000 housing unit, while in the 5 hurricane force impacted census tracts in Mississippi the average personal business line loss is $23,550. This difference cannot be explained by wind speed alone since for Alabama the average census tract wind speed was higher at 35.5 m s^{-1} than the corresponding value for Mississippi at 33.9 m s^{-1}. These values compare to a mean duration of 1.34 h in Alabama and 1.55 h in Mississippi and a mean directional uniformity of 0.41 in Alabama and 0.50 in Mississippi. This result suggests that at the local-scale direct property losses may be more highly correlated with the time-varying wind field than maximum wind speeds alone, in agreement with Powell et al. (1995).[14]

[14] While the duration result is in agreement with Powell et al. (1995), the directional uniformity result contradicts Powell et al.'s findings and is explored later in this section.

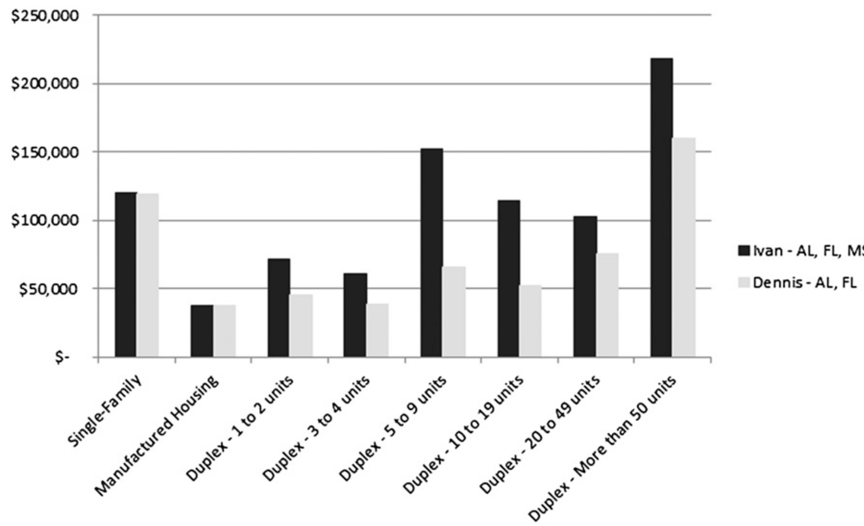

FIG. 5. Average residential building values per hurricane force impacted tracts.

Since the study of hurricane losses is a multicausal hazard, exposure, and vulnerability problem, a statistical analysis that captures and quantifies these effects jointly is appropriate. Therefore, we conduct a multivariate regression analysis of personal line hurricane losses at the hurricane force census tract level from both Ivan and Dennis. Specifically, the empirical model is a semilog OLS model with the natural log of census tract losses against a vector of hazard, exposure, and vulnerability explanatory variables. Figure 6 displays the census tract average hazard and exposure data for both Ivan and Dennis and shows our sample size of 249 census tracts covers a broad range of wind speed, wind duration, wind directional change, and residential exposure values suitable for performing a quantitative analysis of their relative importance to loss. It is also interesting to note clustering of data points associated with the high density of census tracts in urban areas.

First, PCS state losses by personal business line are downscaled to the hurricane force census tract level using two approaches: 1) uniformly distributed across hurricane force impacted tracts in each state and 2) weighted based upon the percentage of total housing units in the hurricane force impacted tract as a proportion to the state total housing units in the hurricane force tracts. Klawa and Ulbrich (2003) assessed losses by population numbers in individual districts, but in agreement with Collins and Lowe (2001) we assume housing units is a more suitable proxy for exposed value since housing units may exceed population growth in coastal regions.

Results from these two analyses are reported in Tables 6 and 7. In each table we run four different models: model 1 only incorporates maximum wind speed; model 2 only incorporates duration; model 3 only incorporates directional uniformity; and model 4 incorporates all three hazard variables simultaneously. Furthermore, as we are most interested in the relative importance of the hazard variables and to avoid the inherent multicollinearity issues in each model 4, the hazard variables are entered in a discrete fashion (Fronstin and Holtmann 1994; Sadowski and Sutter 2005) using thresholds based upon the descriptive loss data results from Powell et al. (1995).[15] High wind speed = 1 when the mean census tract value $\geq 38.6\,\mathrm{m\,s^{-1}}$, 0 otherwise; high duration = 1 when the mean census tract value $\geq 1.67\,\mathrm{h}$, 0 otherwise; and low directional uniformity = 1 when the mean census tract value ≤ 0.45. Following Powell et al. (1995), we expect high wind speed, high duration, and low directional uniformity tracts to all be positive drivers of higher hurricane losses in comparison to the low wind, low duration, and high directional uniformity tracts.

For consistency with the descriptive analysis in section 4a, additional exposure and vulnerability variables included in the estimation (with the expected coefficient sign in parentheses) are the population per square mile (+); the total number of housing units (+); the percentage of housing units that are owner occupied (−); age of the median year housing built (= 2004 or 2005 minus median age of the tract) (+); and the average dollar of exposure value (= total exposure value/total units) for single-family dwellings (+), manufactured

[15] Results reported in these tables are robust to the hazard variables employed in a linear continuous fashion in models 1–3 as well as to other high and low cutoff points based upon the median distribution of the continuous variables. Given the discretization of our hazard variables, we are not estimating a log–log functional form.

TABLE 5. Hurricane Ivan view of combined personal business line loss per state and exposure data.

Hurricane Ivan impact by state	Percentage of total Ivan loss	Percentage of state loss by personal business line	Number of hurricane force wind impacted tracts	Mean of sustained wind in hurricane force (HF) tracts ($\mathrm{m\,s^{-1}}$)	Avg personal loss per HS unit/avg exposure per house × \$1,000	Hypothetical loss per \$200,000 housing unit	Mean of H*Wind duration (hours) in HF tracts	Mean of directional uniformity in HF tracts
Florida	60%	67%	74	38.6	\$158.65	\$31,730	3.05	0.52
Alabama	25%	85%	149	35.5	\$52.48	\$10,495	1.34	0.41
Mississippi	1%	76%	5	33.9	\$117.75	\$23,550	1.55	0.50
Total	100%	72%	228	36.5	\$108.82	\$21,763	1.90	0.44

housing (+), duplex units (+), and other residential types (+). Duplex units are summed across all types from 1 to 2 units to more than 50 units. Other residential types include temporary lodging, institutional dormitories, and nursing homes.

Tables 6 and 7 show that, in controlling for exposure and vulnerability factors, all of the hazard variables considered, not just maximum wind speed, are statistically significant drivers of hurricane losses at the 1% level. High wind speed and high duration tracts are positive drivers of higher hurricane losses in comparison to low wind and low duration tracts as expected. For example, the coefficient values from Table 7 indicate that losses in high wind and high duration census tracts are approximately 166% higher on average than those in low wind and low duration census tracts. However, our analysis indicates low directional uniformity is a negative driver of higher hurricane losses in comparison to high directional uniformity tracts, an unexpected result in comparison to Powell et al. (1995). Comparing models 1 and 2 in both Tables 6 and 7, high wind and high duration variables are comparable in magnitude (approximately 0.98) in inducing higher losses per tract on average, but model 2, which incorporates high duration only, explains more of the overall variation of losses.

When all physical variables are included simultaneously (Table 6 and 7, model 4), high duration is the most relatively significant hazard driver of higher hurricane losses with coefficient value that is approximately 1.5 times larger than that on high wind. Of course, this result is dependent upon our model specification as well as the threshold levels utilized for our hazard variables, and high wind speed is still a significant driver of losses at the 1% level. Nonetheless, the results from a likelihood ratio test between models 4 and 1 show that adding high duration and low directional uniformity to our models results in a statistically significant improvement in model fits than just using wind speed alone [Table 6: LR chi2(2) = 99.87, Prob > chi2 = 0.0000; Table 7: LR chi2(2) = 35.23, Prob > chi2 = 0.0000].[16]

For the exposure and vulnerability variables, coefficient signs as mostly as expected albeit with little statistical significance in the models from Table 6. Average duplex exposure value (−) and average other residential value (+) are the most consistent statistically significant drivers of losses across all four models. From Table 7 we see greater statistical significance in other exposure and vulnerability variables such as average single-family

[16] Likelihood ratio (LR) tests are calculated using nonrobust standard errors.

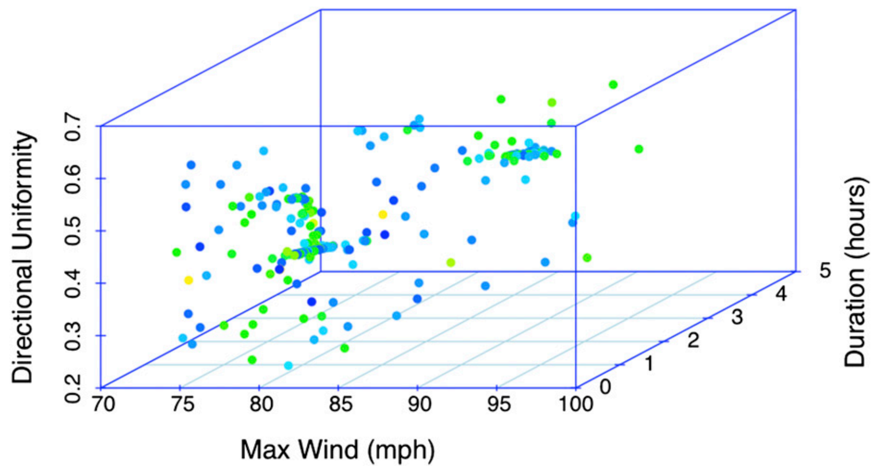

FIG. 6. Scatterplot of impacted census tract average wind speed, wind duration, and directional uniformity colored by residential exposure value (warmer colors indicate higher value) for the 249 hurricane force impacted census tracts for Ivan and Dennis.

exposure value and average manufactured housing exposure value. Assigning tract losses weighted by exposure is likely a driver of these results. However, exposure and vulnerability factors certainly play a role in these hurricane losses.

Finally, as a further robustness check we run a series of analyses on model 4 in Table 7 to account for the potential of omitted variable bias and spatial dependencies in our data stemming from any spatial characteristics that are determinative of hurricane loss amounts but that are not explicitly specified in our statistical estimations.[17] Model 1 in Table 8 controls for spatially oriented omitted variables through the use of county-level fixed effects via nine county dummy variables (Baldwin County, Alabama, is the omitted county dummy). Hurricane losses are also likely spatially dependent in that nearby losses are more alike than more distant losses because of the relatively clustered geographic impact of the wind field characteristics and the potential for windborne debris, as well clustered housing characteristics such as values, construction type, and home age. Lagrange multiplier and robust Lagrange multiplier results based upon the county fixed effect model 1 indicate the use of a spatial lag model to incorporate these spatial dependency issues. In Table 8, model 2, we first run a spatial lag model without any corresponding county fixed effects, while model 3 incorporates the elements of both models 1 and 2 via a full spatial lag fixed effect model estimation. Finally, in model 4, the collinearity between wind, duration, and directional uniformity is further explored through the eight various interactions of high and low hazard variables with low wind, low duration, and high directional uniformity the omitted category.

Incorporating county-level fixed effects further highlights the importance of high duration in the loss analysis (model 1 in Table 8) with high duration coefficient estimates significant at the 5% level, now the only significant estimates of the three hazard variables. The results from a likelihood ratio test between model 4 in Table 7 and model 1 in Table 8 show that adding the county-level fixed effects results in a statistically significant improvement in model fit [LR chi2(2) = 103.19, Prob > chi2 = 0.0000] with three of the county dummies significant at the 1% level. A spatially lagged dependent variable model assumes that the spatially weighted sum of census tract losses enter as an explanatory variable in the estimation represented by rho and is estimated via maximum likelihood techniques.[18] Again, the statistically significant high duration result at the 1% level from

[17] Given the uniform spreading of statewide losses used to generate results in Table 6, we limit the spatially oriented analyses to the specifications in Table 7.

[18] The spatial weighting matrix required for the estimation is generated by the shp2dta and spmat commands in StataCorp (2011) 12.1. The elements of a spatial weighting matrix are binary indicators that identify observations within a neighborhood: $\pi_{i,j} = 1$ when observations I and j are neighbors and $\pi_{i,j} = 0$ otherwise. By convention, the diagonal elements of the weighting matrix are set to zero and row elements are standardized such that they sum to one or are interpreted as an average of neighborhood values. We define our neighborhood by contiguity, where census tracts are considered neighbors if they share a common border and utilized a spectral-normalized weighting matrix. Each tract on average had six identified neighbors. The spreg and spatreg commands were utilized for the estimation, with Lagrange multiplier (LM) tests conducted using spadiag.

TABLE 6. Multivariate regression analysis assuming total state loss is spread uniformly over hurricane force impacted census tracts. Model 1 only incorporates maximum wind speed; model 2 only incorporates duration; model 3 only incorporates directional uniformity; and model 4 incorporates all three hazard variables simultaneously. Robust standard errors are not reported. Adjusted R-squared values are estimated without robust standard errors.

Variable	1	2	3	4
Population per square mile	0.000 024 73	0.000 035 89	0.000 053 25[a]	0.000 026 36
Total housing units	-9.921×10^{-6}	-5.525×10^{-6}	0.000 064 54	-2.778×10^{-6}
Percentage owner occupied	0.066 927 25	0.083 989 25	−0.628 011 18[a]	0.062 100 98
Avg single-family dwelling exposure value	0.000 625 53	0.001 184 11	0.002 890 82[a]	0.000 948 75
Avg manufactured housing exposure value	0.000 916 04	0.000 335 48	0.002 151 04	−0.000 169 85
Avg duplex exposure value	−0.000 664 5[a]	−0.000 452 8	−0.001 018 88[b]	−0.000 392 13
Avg other residential exposure value	0.000 039 87	0.000 050 14[a]	0.000 039 54	0.000 040 72[c]
Age of median year housing built	−0.006 155 44	−0.00 345 999	0.001 644 37	−0.001 629 5
High wind speed	0.985 483 84[b]	—	—	0.388 686 71[b]
High duration	—	0.965 226 23[b]	—	0.547 197 36[b]
Low directional uniformity	—	—	−0.775 552 15[b]	−0.312 508 16[b]
Constant	16.442 658[b]	16.146 381[b]	16.806 831[b]	16.367 258[b]
Number of observations	249	249	249	249
R squared	0.4843	0.5635	0.4418	0.6547
Adjusted R squared	0.4649	0.5471	0.4207	0.6387

[a] $p < 0.05$.
[b] $p < 0.01$.
[c] $p < 0.1$.

the spatial lag model 2 highlights the relative importance of high duration to hurricane losses, but here high wind is also statistically significant at the 1% level in these tracts. The statistical significance on rho at the 1% level also indicates the presence of spatial autocorrelation, which has been generally ignored in the hurricane loss literature. The full fixed effect spatial model 3 illustrates similar significance on the high duration variable as models 1 and 2. In models 1 and 3 in Table 8, which incorporate county fixed effects, the sign on low directional uniformity is as was initially expected in contrast to the results from Tables 6 and 7. Finally, in our hazard interaction model 4 we see that the most statistically significant impact to losses occurs in those tracts simultaneously incurring high wind, high duration, and low directional uniformity or high wind, low duration, and low directional uniformity. Spatial dependencies captured through rho and county fixed

TABLE 7. As in Table 6, but assuming state losses are spread according to census tract housing units as a proportion of total state hurricane force impacted housing units.

Variable	1	2	3	4
Population per square mile	0.000 055 3	0.000 065 6	0.000 085 97[a]	0.000 055 03
Total housing units	—	—	—	—
Percentage owner occupied	0.589 636 23	0.617 837 11	−0.244 440 12	0.731 937 33
Avg single-family dwelling exposure value	0.008 404 29[a]	0.008 951 35[b]	0.011 605 54[b]	0.008 301 34[b]
Avg manufactured housing exposure value	0.011 388 07[b]	0.010 758 31[b]	0.013 972 1[b]	0.010 166 96[b]
Avg duplex exposure value	−0.000 315 05	−0.000 084 67	−0.000 822 66	4.859×10^{-6}
Avg other residential exposure value	0.000 052 05	0.000 062 36[b]	0.000 059 26[a]	0.000 055 62[a]
Age of median year housing built	−0.009 842 36	−0.007 228 5	−0.006 389 99	−0.007 107 54
High wind speed	0.977 787 92[c]	—	—	0.435 244 22[c]
High duration	—	0.979 359 43[c]	—	0.681 789 55[c]
Low directional uniformity	—	—	−0.616 022 84[c]	−0.063 799 97
Constant	14.782 916[c]	14.486 616[c]	15.294 269[c]	14.548 794[c]
Number of observations	249	249	249	249
R squared	0.4675	0.5139	0.3806	0.5377
Adjusted R squared	0.4497	0.4977	0.3600	0.5183

[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

TABLE 8. Robustness checks on model 4 in Table 7.

Variable	1	2	3	4
Population per square mile	0.000 077 14[a]	0.000 063 96	0.000 087 42[a]	0.000 094 92[b]
Percentage owner occupied	0.893 778 06[c]	0.582 788 36	0.830 031 97[a]	0.865 344 17[a]
Avg single-family dwelling exposure value	0.007 854 62[c]	0.008 888 75[b]	0.008 118 07[c]	0.008 211 19[a]
Avg manufactured housing exposure value	0.011 064 03[a]	0.009 527 64[b]	0.010 665 62[b]	0.011 120 58[b]
Avg duplex exposure value	0.000 778 55	−0.000 125 11	0.000 714 02	0.000 744 2[c]
Avg other residential exposure value	0.000 028 02	0.000 054 64[c]	0.000 031	0.000 029 45
Age of median year housing built	−0.001 052 82	−0.007 895 46	−0.001 823 14	−0.000 338 77
High wind speed (HW)	0.133 489 88	0.413 866 96[b]	0.133 539 04	—
High duration (HD)	0.269 773 65[a]	0.680 120 06[b]	0.285 613 54[a]	—
Low directional uniformity (LU)	0.157 734 35	−0.063 257 39	0.151 548 44	—
HW/HD/LU	—	—	—	1.210 944 8[b]
HW/low duration (LD)/LU	—	—	—	0.268 233 43[c]
HW/HD/high directional uniformity (HU)	—	—	—	0.153 342 33
HW/LD/HU	—	—	—	−0.213 431 47
Low wind speed (LW)/HD/LU	—	—	—	0.287 872 95
LW/LD/LU	—	—	—	0.071 091 75
LW/HD/HU	—	—	—	0.130 325 13
Conecuh County, Alabama	−0.345 152 22	—	−0.402 874 14	−0.359 260 23
Escambia County, Alabama	0.069 664 64	—	−0.014 964 37	0.096 759 65
Mobile County, Alabama	−0.409 863 52[b]	—	−0.459 144 68[b]	−0.367 098 5[b]
Monroe County, Alabama	0.144 805 13	—	0.174 704 04	0.284 770 47
Washington County, Alabama	0.440 705 84	—	0.592 932 01[a]	0.663 547 56[a]
Escambia County, Florida	0.694 065 94[b]	—	0.611 270 02[b]	0.875 825 16[b]
Santa Rosa County, Florida	0.981 283 21[b]	—	0.875 006 2[b]	1.064 371 6[b]
Jackson County, Mississippi	0.106 495 88	—	0.226 227 26	0.328 822 11
Constant	14.186 529[b]	14.256 524[b]	14.008 31[b]	13.838 486[b]
Rho	—	0.031 324 2[b]	0.022 525 27[b]	0.024 921 39[b]
Sigma2	—	0.608 966 85[b]	0.498 839 43[b]	0.489 166 85[b]
Number of observations	249	249	249	249
R squared	0.6946	—	—	—
Adjusted R squared	0.6707	—	—	—
Log likelihood	−183.5511	−229.8354	−180.1545	−175.2815
Akaike Information Criterion	405.1022	485.6707	398.3091	394.5629

[a] $p < 0.05$.
[b] $p < 0.01$.
[c] $p < 0.1$.

effects are still consistently statistically significant in this model.

In conclusion, these empirical estimations complement the overall case study analysis by statistically demonstrating the relative importance of the three identified hurricane hazard variables controlling for other exposure, vulnerability, and spatial characteristics of the data. Given the limited census tract sample size and a number of assumptions in the construction of our dataset, we caution against interpreting the coefficient results too literally in terms of the exact magnitude of losses for Ivan and Dennis. However, the consistent statistical significance of high duration across the specifications (or in combination with the other hazards) suggests an important role for hurricane wind field characteristics other than maximum wind speed in determining losses.

6. Summary and discussion

A deeper understanding of the potential drivers of local-scale hurricane losses has been developed through a case study analysis contrasting two recent category-3 U.S. landfalling hurricanes (Ivan in 2004 and Dennis in 2005). Although similar in terms of maximum wind speed at their proximate coastal landfall locations, these hurricanes caused vastly different loss amounts. State-level raw wind insured loss data split by personal, commercial, and auto business lines were downscaled to the census tract level using the assumption that maximum wind speeds above threshold values define the impacted tracts. In contrast to existing studies that assess loss mostly at the aggregate level, these local-scale data were used to systematically explore the nature of the relationship between hazard, exposure and vulnerability factors to loss. At this level of detail, our main findings are as follows:

1) Losses extend far inland beyond coastal counties and losses are spread across business lines. This suggests that the commonly used approach of making simplifying assumptions of loss confined to affected and/or coastal counties and normalizing loss by specific exposure factors that represent only a single business line can significantly misrepresent the true underlying localized loss, exposure, and vulnerability data.
2) Hurricane force winds for Ivan extended over an area 5 times greater than those for Dennis, and it seems likely that this difference in impacted area explains a large portion of the loss difference. Storm size not only controlled the size of the impacted area but also contributed to differences in the distributions of census tract average wind speed, wind duration, and wind directional change within the impacted area.
3) Analysis of exposure and vulnerability attributes within the impacted census tracts showed large differences between storms, thereby highlighting other potential drivers of loss. In particular, impacted building counts, building density, and building age were notably different between storms.
4) Census tract average personal losses summed by state did not increase monotonically with tact average maximum wind speed. Rather, loss increased monotonically with duration of hurricane force winds and directional uniformity.
5) An empirical analysis of census tract-level losses (generated by downscaling state losses using the assumption of either uniform spread over impacted tracts or weighted by proportion of total impacted housing units) showed that, when controlling for other exposure and vulnerability factors, all of the hazard variables utilized, not just maximum wind speed, are statistically significant drivers of census tract hurricane losses at the 1% level. Further, when all physical variables are included simultaneously in the estimation, high duration is the most relatively significant driver of higher hurricane losses, and the addition of high duration and low directional uniformity results in a statistically significant improvement in model fit than just using wind speed alone. Additional robustness checks incorporating the spatial nature of the data in the estimation confirmed the statistically significant role of wind field variables other than maximum wind speed.

In summary, both descriptive and quantitative evidence is provided that the addition of wind duration and directional change may improve loss estimation. The physical mechanisms by which duration contributes to loss include the following: increased likelihood of dynamic loading, fatigue through repeated stress cycles, increased probability of debris impacts, and increased likelihood of wind-driven rain losses. Directional change contributes to loss by increasing the likelihood of a structure experiencing loading from a direction of highest vulnerability. Since the role of size is in not only determining the size of affected area but also in determining how long damaging winds last for a given location and the likelihood of locations experiencing high degrees of directional change, the addition of storm size to hurricane impact indices such as the Carvill hurricane index (Kantha 2006; Smith 2006) may go a long way in accounting for the more detailed factors examined here. Descriptive evidence is provided that readily available building counts, building density, and building age data may further improve local-scale loss estimation.

Appropriate consideration of these local drivers of hurricane loss may improve historical loss assessments, and it is possible that these local drivers may also act upscale to impact future projections of hurricane losses under climate and socioeconomic change. Extensions to this work will include other case studies not only to increase sample size and drive a larger statistical model of losses but also to explore the potential to explain hurricane losses using other exposure, vulnerability, and human behavioral factors and assess the relative importance of each across scales.

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