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Research

Coupled human-natural system impacts of a winter weather whiplash event

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ABSTRACT. In October 2011, the Halloween Nor'easter produced unusually early and heavy snowfall while leaves were still on the trees, causing extensive damage throughout the northeastern United States. This storm is an example of winter weather whiplash, in which an abrupt, back-and-forth swing in winter weather affects coupled human and natural systems. Research on the social-ecological drivers and impacts of winter weather whiplash is scarce because most studies only consider meteorological causes and consequences of extreme events. In this study, we used publicly available data of snowfall accumulation, vegetation phenology, road density, and per capita income to predict storm impacts, which we estimated with textual analysis of Halloween Nor'easter newspaper coverage. We demonstrated that a combination of meteorological, natural, and human system drivers was better able to predict the impact of the storm than meteorological drivers alone. Although we focused on the Halloween Nor'easter, our work highlights the necessity of understanding how multiple drivers and hazards can intersect to create rare and possibly novel conditions that may become more common as the climate warms and becomes more variable.

Key Words: *climate change; compound extremes; coupled natural and human systems; vulnerability; winter weather whiplash*

INTRODUCTION

On 28 October 2011, a cold polar air mass encountered a low-pressure system off the southeastern coast of the U.S., forming a Nor'easter that moved northward to the Canadian Maritimes. Rain fell during the morning of 29 October and changed to snow during the hours from the 29th through the 30th (Ryan 2011, LeComte 2012). Historical snow accumulation records were broken at multiple locations (NOAA 2021). The storm resulted in ~4.3 million people losing power, and total damage estimates were US$1 to 3 billion (DOE 2011, FERC 2012). The timing of the event was unusual and contributed to the magnitude of its impact because accumulating snowfall typically does not occur in most of the northeastern U.S. until late November (Contosta et al. 2019). Average monthly temperatures from September through November 2011 were higher than normal (Contosta et al. 2019), resulting in delayed autumn senescence (Yue et al. 2015), particularly for species that experience later leaf coloration and abscission such as American beech (*Fagus grandifolia*), white oak (*Quercus alba*), and red oak (*Quercus rubra*; Lee et al. 2003). Heavy snow loads on deciduous trees still in-leaf rendered them vulnerable to storm damage (FERC 2012). Prior extreme weather events in the region that year, including a tornado outbreak (June 2011) and Hurricane Irene (August 2011), had already caused extensive power outages (LeComte 2012, Kloster et al. 2019) and power outage "fatigue" among residents (e.g., Johnson and Wojtas 2011).

This "Halloween Nor'easter" illustrates weather whiplash: a type of extreme event that features a seesaw in weather conditions. Definitions of weather whiplash vary. They include rapid shifts in precipitation from anomalously dry to anomalously wet conditions over seasonal (Swain et al. 2018) and interannual (He and Sheffield 2020) timescales. They also include rapid swings in surface temperature over weekly, daily, and diurnal (24 hour) periods (Lee 2022). From an atmospheric standpoint, weather whiplash can manifest as an abrupt shift from a persistent circulation pattern into a new circulation regime that may or may not endure (Francis et al. 2022). Although early season snowstorms can occur in the Northeast, the 2011 Halloween Nor'easter has characteristics of weather whiplash that set it apart from other out-of-season events. Temperatures across the Northeast from September through November of 2011 were persistently warm, averaging 1.5 to 5 °C higher than normal. This weather pattern was interrupted by the convergence of a cold polar air mass colliding with warmer air off eastern North America, such that temperatures dropped as much as 5 to 10 °C during the storm before rebounding to pre-storm values (Vose et al. 2014, NOAA 2023). In this case, the rapid back-and-forth change in temperature included shifts from above to below freezing and then back above 0 °C once the storm passed. According to Casson et al. (2019), this repeated crossing of the 0 °C threshold makes the Halloween Nor'easter a winter weather whiplash event that has the potential for outsized impacts (Fig. 1; Mazdiyasni and AghaKouchak 2015, Zscheischler and Seneviratne 2017).

Outsized consequences of winter weather whiplash occur in part from the transition from frozen to thawed conditions (or vice versa) because the phase change of water can damage natural and managed vegetation, cause catastrophic flooding, and destroy physical infrastructure such as roads and power lines (Casson et al. 2019, Zscheischler et al. 2020). The social-ecological context in which winter whiplash events occur contributes to their effects. For example, emergency response capability, local awareness of risk, and floodplain development policies can magnify or mitigate the effects of weather extremes on local communities (Das et al. 2018). Therefore, in addition to synoptic-scale meteorology (i.e., weather events on the scale of days and across hundreds or thousands of kilometers), the unique social-ecological setting of the Halloween Nor'easter likely exacerbated the scope of its impacts.

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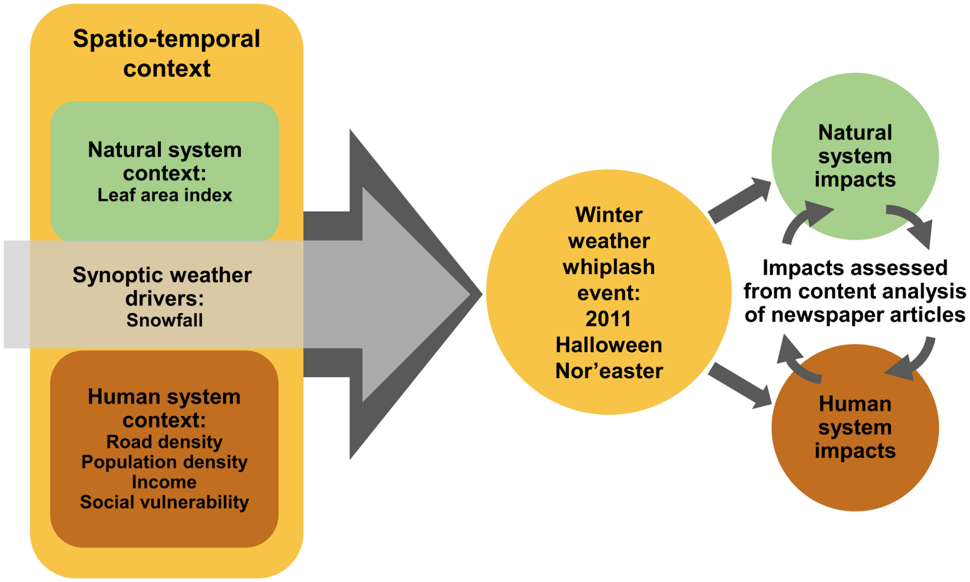
Fig. 1. Conceptual framework of the 2011 Halloween Nor'easter winter weather whiplash event (modified after Casson et al. 2019).



METHODS

Our study area comprised states in the geographic footprint of the Halloween Nor'easter, which extended across the northeastern U.S. from Virginia to Maine. Within this footprint, we compiled publicly accessible data on the meteorological, natural system, and human system drivers and impacts of the storm (Fig. 2). Variable selection was guided by our conceptual model of winter weather whiplash (Casson et al. 2019; Fig. 1), which situates ecological disturbance theory within a coupled human and natural systems framework to emphasize interactions between regional-scale weather events, the social-ecological setting in which events occur, and the resulting impacts. We used a "bottom-up" approach (sensu Zscheischler et al. 2018) in choosing driver and impact variables for the analysis, starting with the event itself and then identifying the factors, processes, and phenomena that shaped the outcomes of the event. This kind of approach emphasizes combinations of drivers and hazards that result in system failures while also enabling an analysis of the relative importance of different drivers in causing specific impacts. Both driver and impact variables were scaled or aggregated per county within the study area. All spatial analyses were performed in ArcGIS version 10.4.1.

Driver variables

Synoptic weather

We considered snowfall the primary synoptic weather driver of the event (Fig. 1). Spatial 24-hour snow water equivalent (SWE) accumulation data (inches) for each day of the October snowstorm (28 to 31 October 2011) were obtained from the 0.04-degree resolution National Snowfall Analysis product (NOHRSC 2021). To estimate snow accumulation, SWE values for all four days were summed at each pixel location, filtered to remove pixels with less than one-inch accumulated SWE (NOAA 2021), averaged for all pixels within each county, and then converted to mm.

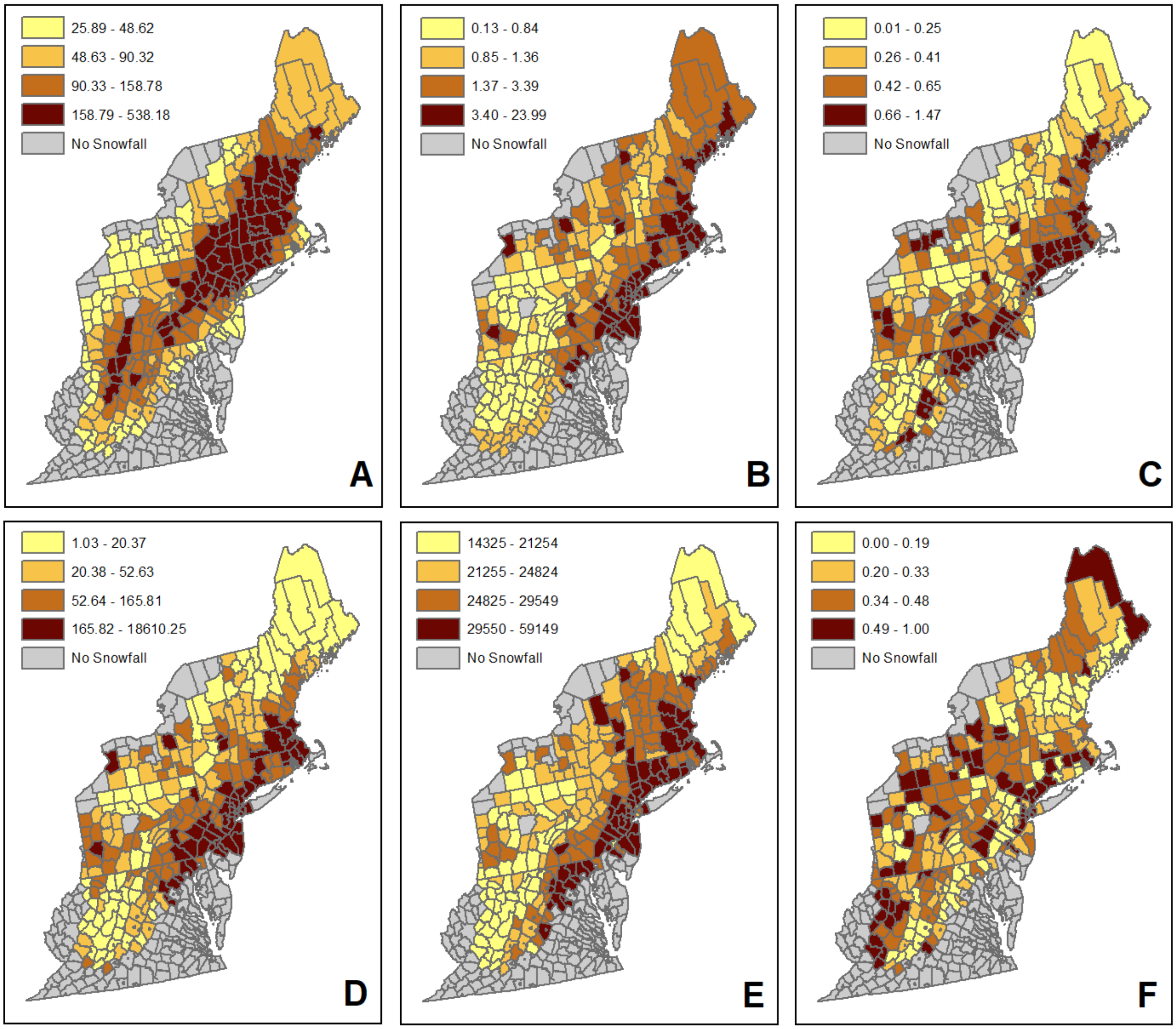
Natural system context

The presence of leaves greatly increases the probability of tree damage during snowstorm events as the mass of snow that can accumulate is greater because of the larger surface area than the branches alone (Kane and Finn 2014). Therefore, we selected leaf area index (LAI) immediately prior to the storm as the natural system driver of the event (Fig. 1), where LAI is a dimensionless quantity of leaf area per unit ground area that characterizes the density of leafed tree canopies. Spatial LAI values for 28 October 2011 were obtained from the 1-km resolution Moderate Resolution Imaging Spectrometer (MODIS) MCD15A3H data product (Friedl et al. 2010, Myneni et al. 2015), cropped to the study area, and then averaged for each county.

Human system context

We selected four variables as human system drivers: road density, population density, per capita income, and the social vulnerability index (SVI; Fig. 1). In keeping with Winkler et al. (2010), road density was used as a proxy for above-ground power line density—the infrastructure that was most commonly, extensively, and heavily damaged in the event—because we did not have private, utility-owned power line maps across the region. Road density was calculated from the U.S. Census Bureau's TIGER/Line Files and Shapefiles spatial dataset of primary and secondary roads for 2011 (USCB 2011). The dataset was filtered to remove primary roads—divided and limited-access highways—because secondary roads typically comprise the electric distribution network (e.g., Short 2003). These secondary roads were spatially joined to each county to associate each road segment with a specific county. The lengths of the road segments per county were calculated in kilometers, summed per county to obtain total road lengths, and then divided by county area to yield road density per county (km/km^2). We obtained total population counts and SVI scores for 2010 and per capita income (US$ 2010) at the county level from the U.S. Centers for Disease Control and Prevention (CDC 2010). Total population per county was divided by county area to obtain

Fig. 2. Maps of driver variables per county. (A) Average 4-day snowfall accumulation (mm snow water equivalent [SWE]); (B) Average leaf area index (LAI; unitless) for 28 October 2011; (C) Road density (km/km²); (D) Population density (people/km²); (E) Per capita income in US$ 2010; (F) Social vulnerability index (unitless). Counties in gray did not experience snowfall and were not included in the analysis.



population density (people/km²). Population density is well-correlated with infrastructure density and has been used to assess risk from natural disasters in other studies considering social and ecological contexts (Quinn 2013). The SVI estimates the social vulnerability of U.S. counties to environmental hazards, including extreme weather events, according to variables such as age, income, ethnicity, and housing, and ranks the estimates based on percentiles for all counties within each state to yield scores ranging from 0 (least vulnerable) to 1 (most vulnerable; Flanagan et al. 2011).

Impact variable

We undertook a contextual analysis of newspaper articles reporting on the Halloween Nor'easter to evaluate the impact of the winter weather whiplash event. Data on the social and economic impacts of extreme events can come from a variety of sources, including bulletins from meteorological agencies, retrospective reports from governmental or non-governmental agencies, insurance industry sources, or news agencies (Hilker et al. 2009, Wirtz et al. 2014). Newspaper articles provide detailed, authoritative information throughout an event (Barnolas and Llasat 2007), are particularly useful for capturing information about smaller events that may not be captured in reports focusing on very large events (Du et al. 2015), and provide spatially resolved information if local or regional news sources are available (Gil-Guirado et al. 2019). There are limitations to the types of impacts captured in newspaper articles. For instance, news coverage is contingent on what other newsworthy events are happening at the time (Eisensee and Strömberg 2007), tends to focus on impacts in urban areas (Llasat-Botija et al. 2007), and provides estimates of damages that are preliminary and so may not be complete (Downton and Pielke 2005). We accessed articles reporting on the Halloween Nor'easter using Nexis Uni (https://www.lexisnexis.com/en-us/professional/academic/nexis-uni.page). Initial reference searches focused on synoptic scale weather drivers of the event, using the term "snow," bounded range of dates aligning with storm development and for two weeks after the event (28 October to 12 November), publication type (newspaper), location of story (northeastern U.S.), additional terms ("storm" or "fall"), and location of publication (local, state, or national). Following methods used by Kloster et al. (2019), only those articles that wrote specifically about the snowstorm and its impacts were considered. We included articles about trees or branches (natural system) damaging physical infrastructure such as powerlines (human system) and excluded articles if there was no perceived impact beyond brief weather references. Further, all remaining articles about unrelated events occurring at that time were excluded. Only articles located in their original sources of publication were considered; all others were removed (Kloster et al. 2019).

We applied content analysis as the method for coding newspaper articles (Adler and Clark 1999, Kloster et al. 2019); coding and subsequent analysis was completed using NVivo 10 software. A coding frame was developed based on our understanding of the storm as a winter weather whiplash event (Fig. 1) in combination with a preliminary review of newspaper articles in our dataset. This frame resulted in seven themes that aligned with our conceptual framework (Fig. 1): "weather," "tree damage," "power," "public safety," "community response," "local events," and "other impacts." "Weather" referred to the meteorological driver of snowfall as well as to comparisons of the storm to previous October snowfalls. "Tree damage" referred to downed trees or branches; a key natural system impact of the 2011 Halloween Nor'easter event was tree damage from snow accumulation weight on leaves. The other five themes represented human system impacts. "Power" included references to power outage, restoration, and the number of customers without power per county. The theme of "public safety" encompassed avoided travel, accounts of personal injury in traffic accidents or at home, and state emergency declarations that cautioned against travel. "Community response" reflected community interventions such as the provision of temporary shelter. "Local events" represented individual events that were cancelled because of the storm, such as Halloween trick-or-treat—a direct and cultural impact of the storm. "Other impacts" was established to represent impacts that were broader-ranging or did not fit completely within the local event category. The frequency with which these themes appeared enabled us to qualitatively assess the degree of focus of our conceptual model components (Fig. 1) in the news media. Once the initial coding was completed, a subset of articles was systematically checked by a second researcher well-versed in social science methodology to ensure consistency in coding (e.g., Kloster et al. 2019).

We delineated the geographic impact of the Halloween Nor'easter by assigning articles to counties through direct references in the article to the counties themselves. If counties were not identified, the articles were assigned to the counties of the communities or municipalities referenced in the articles. Articles without such location information were assigned to the county in which the newspaper was published. We then summed the number of articles and the number of publishing newspapers per county and then divided the total number of articles by the total number of publishing newspapers per county, and this metric was used as the impact variable in our statistical modeling of the event. We standardized the number of observed articles to the number of news sources in a county because our study area covered a range of population densities from very low rural areas to very dense urban areas; without performing the standardization, the dense urban areas would be overrepresented in our dataset.

As described above, there is a well-established body of literature relating the quantity and quality of news coverage after an extreme event to the social and economic impacts of that event. The novelty of our approach is in the number of newspaper articles as the impact (dependent) variable in a random forest model.

Statistical analysis of drivers and impacts on coupled human-natural systems

All statistical analysis was conducted in R 4.0.3 (R Development Core Team 2020). We used regression tree modeling to test our hypothesis that a combination of meteorological, human, and natural system drivers would more accurately predict the impact of the Halloween Nor'easter winter weather whiplash event than meteorological drivers alone. Independent variables were snowfall (synoptic scale meteorological driver), LAI (natural system context), and road density, population density, per capita income, and the SVI (human system context). The impact variable was the ratio of articles to publishing newspapers per county (the impact of the event). The influence of driver variables on the impact variable was modeled with different combinations of the synoptic scale weather (snowfall), natural system (LAI), and human system (road density, population density, per capita income, and SVI) drivers. Snowfall, which was the driver variable representing the primary cause of snow-related impacts, was included in every driver variable combination. Per capita income and SVI were not used in the same models because of collinearity. Model comparison was performed by calculating the Akaike's Information Criteria (AIC) for each regression tree model using the "regclass" package (Petrie 2020). The model with the lowest AIC explained the maximum amount of variation with the fewest number of drivers.

The driver variables from the optimal regression tree—as determined from multi-model inference using the AIC—were then used in a random forest analysis to determine the relative importance of each driver and to generate county-level predictions of impact. Random forest is a machine learning algorithm that uses an ensemble of decision trees to predict a dependent (impact) variable from a suite of independent (driver) variables (Liaw and Wiener 2018). It makes no assumptions about data distributions, can incorporate both continuous and categorical variables, and can accommodate collinearity between variables (Liaw and Wiener 2018). Previous research has applied random forest modeling to a variety of natural resource management contexts, such as evaluating how biophysical and social factors influence roadside vegetation management to minimize power outages (Hale and Morzillo 2020). The relative importance of each driver in the random forest models was assessed by calculating the mean squared error for each tree, comparing its predictions with observed values for a subset of the data, and then averaging the percent of variance explained in the impact variable across 10,000 trees to produce an estimate of model-averaged fit (Liaw and Wiener 2018). Random forest analysis was completed using the R package "randomForest." The predicted storm impacts from the random forest analysis were mapped by county to visually compare them with the observed impacts. Partial dependence plots were then used to assess the impact of each driver on the perceived impact of the storm.

RESULTS

From 28 to 31 October 2011, total snowfall ranged from 0 to 60 mm SWE across the region. The highest snowfall occurred in a band that extended from southeastern Pennsylvania to southern New Hampshire, with most counties in Massachusetts receiving some of the most significant snowfall of the storm (Fig. 2A). Leaf area index, which represented the natural system context in which the system occurred, was highest in coastal and urban counties along the eastern seaboard (Fig. 2B). Likewise, the human system variables of road density and population density were generally greater along the coast and in major metropolitan areas such as Philadelphia, New York, and Boston (Fig. 2C and 2D road density and population density, respectively). Per capita income ranged from US$14,325 to $59,149 2010 across the region and was generally higher along the coast in the Washington, D.C. to Boston area and lower in the rural areas and in particular West Virginia, upstate New York, Pennsylvania, and Maine (Fig. 2E). The social vulnerability index had a large range, from as low as 0.002 in the Washington, D.C. to New York suburbs and parts of New Hampshire, Maine, and Vermont to as high as 0.998 in New York City (Fig. 2F).

Our initial search of newspaper articles covering the storm (integrated metric of meteorological, natural, and human system impacts) resulted in 361 articles. After restricting the articles to only those in their original publication source and which were about the storm and its direct impact on people and property, 121 articles remained from which we analyzed the consequences of the Halloween Nor'easter. The ratio of articles to publishing newspapers per county ranged from 0 to 21 (Fig. 3A). There were as many as nine newspapers per county publishing these articles and as few as zero (Fig. 3B). The geographic range of both the number of articles and the number of newspapers generally mirrored the spatial distribution of total snowfall, though areas of greater coverage also occurred in counties outside of the epicenter of the storm.

Content analysis of the 121 newspaper articles in our dataset revealed that "weather" was the most frequently identified of the seven themes in our coding frame (n = 224), with multiple locations referenced in a single article occurring several times. Coverage related to "weather" highlighted the record-breaking amount of snowfall that the storm produced as well as the fact that the snow was wet and heavy (see Table 1 for representative quotes for all seven themes). "Power" was the next most common theme (n = 180), followed by "public safety" (n = 103). Impacts related to "power" emphasized the extent of power loss and the deployment of crews from across the U.S. and Canada to restore electricity to the region. Articles that discussed "public safety" noted both the danger of traveling on roads during the storm as well as the hazards of live power lines on the ground and in trees following the storm. The next most frequent theme was "tree damage" (n = 66). Newspaper content related to "tree damage" impacts described the breaking and falling of trees and limbs onto roads and houses, resulting in dangerous driving conditions and damage to homes and personal property. Media coverage of "community response" (n = 57), another human system impact, focused on shelters for residents who had lost electricity. The themes of "local events" and "other impacts" had the fewest references in our dataset (n = 60 and 7, respectively). Content related to "local events" emphasized the cancellation of trick-or-treating, while text describing "other events" noted broader-ranging and multi-day impacts such as school closures, changes to school year calendar because of closures, and changes to or extensions made for university admission deadlines.

Fig. 3. (A) Ratio of articles to publishing newspapers per county; (B) Number of publishing newspapers of those articles in A; (C) Observed impact of the storm expressed as the number of articles divided by the number of publishing newspapers; (D) Predicted impact of the Halloween Nor'easter. Counties in gray did not experience snowfall and were not included in the analysis.

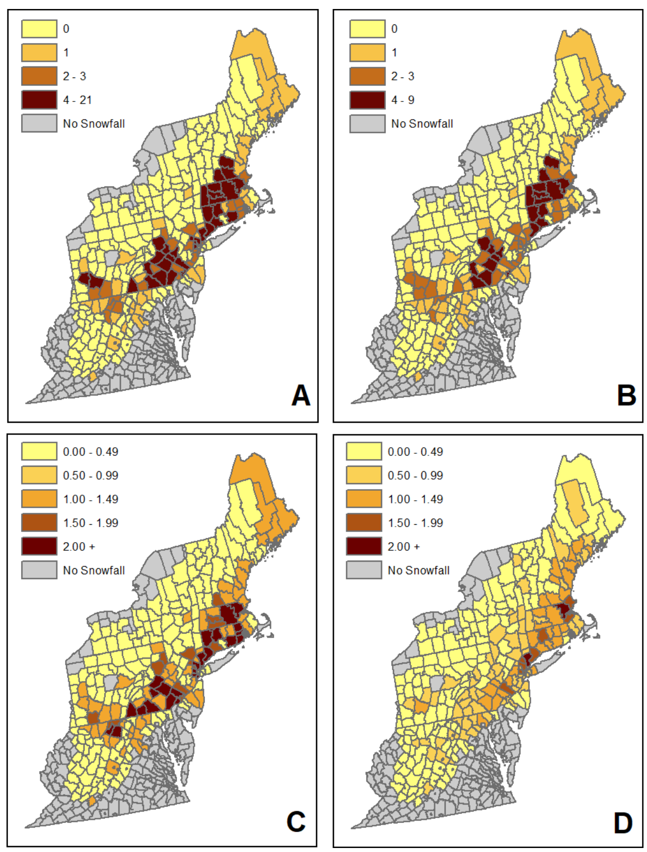


Table 1. Representative quotes describing meteorological, natural, and human system impacts of the Halloween Nor'easter as determined through newspaper content analysis; themes are ordered by frequency of occurrence.

Theme	Representative quote
Weather	"... the weather service spokesman said the snowstorm 'absolutely crushed previous records that in some cases dated back more than 100 years.' Saturday was only the fourth snowy October day in New York's Central Park since record-keeping began 135 years ago" ("3 million in dark in Northeast snow," *Charleston Gazette*, Charleston, WV, 31 October 2011).
	"It's not only a lot of snow, but a lot of the heaviest wettest snow that you ever want to see out there" ("Storm knocks out power for 110,000," *Cape Cod Times*, Hyannis, MA, 30 October 2011).
	"The Saturday snow, with an official depth of 5.5 inches, more than doubled the cumulative total of 3.5 inches of all known October snowfalls in the record period, which dates to 1869" ("Record snow was October surprise," *Reading Eagle*, Reading, PA, 4 November 2011).
Power	A Connecticut Light & Power spokeswoman said, "the utility doesn't know when power will be restored as it struggles to deal with a storm that cut power to 820,000 of its 1.2 million customers" ("Greenwich continues storm cleanup," *The Stamford Advocate*, Stamford, CT, 31 October 2011).
	"State officials said 1,500 crews are working to restore power, including workers called in from as far away as Texas, Louisiana, Michigan and Canada" ("For many, It's far from over," *Sentinel & Enterprise*, Fitchburg, MA, 1 November 2011).
	"Since Saturday, local and regional linemen have struggled in 16-hour shifts to repair powers lines damaged by tree branches weighed down by wet snow and leaves. 'It's called cracking ... ' 'This storm hit when not all the leaves had fallen, and that extra weight causes the branches to crack and fall on the lines ... The biggest challenge are the trees ... When the branches come down, they snap the lines in half' "("Out-of-state electric workers up early to help restore power in York County," *York Daily Record*, York, PA, 2 November 2011).
Public Safety	"The storm is causing treacherous driving conditions ... 'I am urging residents to stay off the roads and let DOT crews get out there and get the streets clear ... People should stay inside at this point, we are seeing heavy snow start to impact power as well as driving' " ("Power lines and trees fall as nor'easter dumps snow on Stamford," *The Stamford Advocate*, Stamford, CT, 30 October 2011).
	"... urged everyone to stay far away from downed lines and trees, since storms like this can lead to live power lines being on the ground. 'Be sure to keep pets and children especially away from downed lines, and be very careful around trees and tree limbs that have come down that may have power lines tangled in them' " ("Storm knocks out power," *Lowell Sun*, Lowell, MA, 2 November 2011).
Tree Damage	"Crack! Boom! Trees were going down as I was driving" ("Halloween horror show," *Lowell Sun*, Lowell, MA, 31 October 2011).
	" 'My house is decimated,' said ..., who had three trees that fell in her yard from the weight of the snow ("Halloween horror show," *Lowell Sun*, Lowell, MA, 31 October 2011).
	" 'The whole back of my house is a wooden mess,' he said Monday afternoon from the kitchen of his home. 'I've called some tree companies but all of them seem to be busy. What a way to wake up.' His backyard is littered with branches and debris, and the bulk of the tree is still sitting on the top of his house. He's already contacted his insurance company, but he said not much can be done until the tree is removed! ("For many, 'It's far from over'," *Sentinel & Enterprise*, Fitchburg, MA, 1 November 2011).
Community Response	"But because of the continuing widespread outages, 77 shelters were open across the state as of last night" ("Wintry mid-autumn storm sweeps Western Mass., recovery begins," *Massachusetts Daily Collegian: University of Massachusetts - Amherst*, Amherst, MA, 1 November 2011).
	"The American Red Cross opened a shelter Monday afternoon at the Lebanon Valley Expo Center, 80 Rocherty Road, North Cornwall Township, to serve people in Lebanon County and the northern end of Lancaster County who were without power. Meals, showers and cots were available for anyone who needed help. Two people were at the shelter Monday night" ("Red Cross takes in storm victims at Lebanon Valley Expo Center," *The Lebanon Daily News*, Lebanon, PA, 31 October 2011).
Local Events	"When I found out Halloween was canceled, I was so bummed; it was the worst day ever ... I went over to my grandparents' house in New Milford because they were, like, the only people on the planet who had power. But we still didn't get to go trick-or-treating. There were too many trees and wires all over the place. So I sat there on the couch and did nothing. I said, 'I can't believe it's Halloween and I'm sitting on a couch! This is an outrage!' " ("For Some, Halloween in November Is a Sour Idea," *The New York Times*, New York City, NY, 4 November 2011).
	"In Sherman, Conn., ... and her daughter, ..., 7, spent Halloween night and the next night at a makeshift shelter. But they got a little trick-or-treating in Monday and will attend Halloween events at schools Friday night and Saturday" ("For Some, Halloween in November Is a Sour Idea," *The New York Times*, New York City, NY, 4 November 2011).
Other Events	"Connecticut schools must have at least 180 days of classes during the academic year and finish by June 30 under state law. Many districts have already lost five to 10 days of classes and used up most of the snow days they set aside as a cushion ... West Hartford Assistant Superintendent ... said the school year is now scheduled to end around June 20 or 21 unless more snow days push it later" ("East loses school days to snow, storm; Costal states worry about making up days after heavy snowfall, Irene," *Charleston Daily Mail*, Charleston, WV, 4 November 2011).
	"Dozens of colleges and universities nationwide, meanwhile, extended their early decision deadlines because of the snowstorm, as the widespread power failures made it impossible for many students to email their applications by the Tuesday deadline" ("East loses school days to snow, storm; Costal states worry about making up days after heavy snowfall, Irene," *Charleston Daily Mail*, Charleston, WV, 4 November 2011).

Regression tree analysis showed that the geographic impact of the Halloween Nor'easter, as quantified by a number of newspaper articles per county, was best modeled using a combination of meteorological, human, and natural system drivers (no other model had a ΔAIC of < 2). Multi-model inference indicated that the model that included snowfall, LAI, road density, and per capita income as driver variables had the lowest AIC and the highest r^2 of any model in our suite (AIC = -284.72, r^2 = 0.54; Table 2). A base model including snowfall (meteorological driver) as the only driver had an r^2 value of 0.28. Adding LAI (natural system driver) to this base model improved the model r^2 to 0.35. Adding road density, population density, and per capita income (human system drivers) to the base model improved the model r^2 to 0.50.

Table 2. Results of regression tree analyses using different combinations of driver variables (meteorological, natural system, and human system) to predict the impact of the 2011 Halloween Nor'easter. Models were ranked based on Akaike's Information Criteria (AIC) compared with the base model that included the meteorological variable of snowfall (shown as snow water equivalent or SWE) as the single driver. LAI = leaf area index; Road = road density; Pop = population density; Inc = per capita income.

Predictor types	Variables included	AIC values	r^2
Meteorological + natural+ human	SWE + LAI + Road + Inc	-284.72	0.54
	SWE + LAI + Inc	-260.95	0.50
	SWE + LAI + Pop + Inc	-250.39	0.46
	SWE + LAI + Pop + SVI	-250.39	0.46
	SWE + LAI + Road + SVI	-236.12	0.43
	SWE + LAI + Road	-236.12	0.43
	SWE + LAI + SVI	-216.57	0.38
	SWE + LAI + Road + Pop + Inc	-212.78	0.36
	SWE + LAI + Road + Pop + SVI	-212.78	0.36
	SWE + LAI + Road + Pop	-212.78	0.36
	SWE + LAI + Pop	-212.78	0.36
Meteorological + human	SWE + Pop + SVI	-269.86	0.50
	SWE + Pop	-269.86	0.50
	SWE + Road + Inc	-261.73	0.51
	SWE + Pop + Inc	-261.62	0.48
	SWE + Road	-216.60	0.39
	SWE + Road + Pop + Inc	-212.78	0.36
	SWE + Road + Pop + SVI	-212.78	0.36
	SWE + Road + Pop	-212.78	0.36
	SWE + Inc	-209.90	0.38
	SWE + Road + SVI	-197.46	0.33
	SWE + SVI	-147.94	0.18
Meteorological + natural	SWE + LAI	-205.73	0.35
Meteorological only	SWE	-171.91	0.28

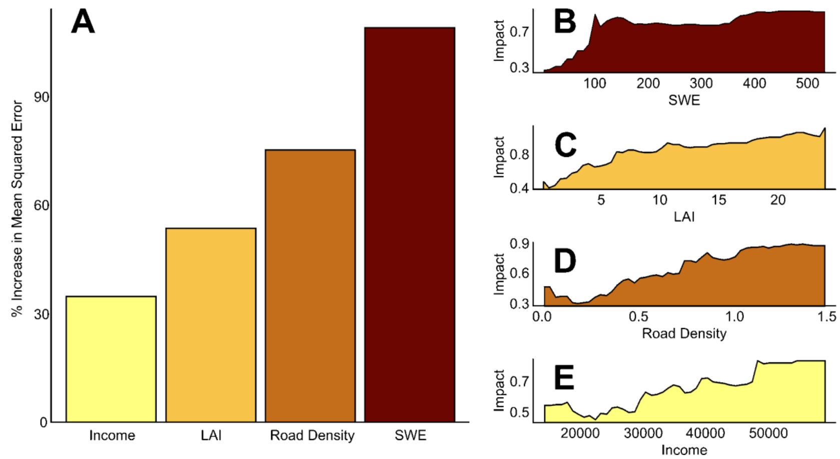
Across the study area, 0 to 3.5 newspaper articles per county reported on the observed impact of the storm (Fig. 3C). We used random forest analysis of the optimal regression tree (see Table 2) to predict the storm impact. The random forest explained 31% of the variance in the impact of the storm (mean squared residuals = 0.47), with the predicted impact varying from 0 to 2.3 (Fig. 3D). The ratio of articles to publishing newspapers per county was over-predicted in low population density areas where the observed ratio was close to or equal to zero, and under-predicted in high population density areas where the observed ratio was greater. A variable importance plot of the random forest analysis showed that snowfall was the most influential variable predicting storm impacts, as determined by the increase in mean squared error (Fig. 4A). The relative importance of the three other drivers in the model were ranked in order of road density, followed by LAI, and then per capita income (Fig. 4A). Partial dependence plots showing the marginal effects of each driver are presented in Figure 4.

DISCUSSION

The example of the Halloween Nor'easter demonstrates that winter weather whiplash events affect coupled human and natural systems beyond what would be expected from weather alone (Mazdiyasni and AghaKouchak 2015, Zscheischler and Seneviratne 2017). In keeping with our hypothesis, we found that regression tree models that combined meteorological, natural, and human system drivers were better able to predict storm impacts than models that considered each driver in isolation. Prior research has taken a similar approach to combining meteorological data with information about natural and human systems to enhance model predictions of extreme events (e.g., Wanik et al. 2015, Cerrai et al. 2019). To our knowledge, our study is unique in analyzing both the drivers and impacts of a compound extreme winter weather event using a social-ecological lens. The quantitative analysis we present here using the number of newspaper articles standardized by the number of sources is a potential model for understanding the impact of these types of events. Although there are limitations to using newspaper articles as a measure of impact, the relatively good fit of the random forest model suggests that, in this case, the newspaper articles captured the geographical distribution of storm impacts. This kind of integrated assessment is crucial to anticipating risks that might arise when multiple hazards overlap to create rare and possibly novel conditions (Balch et al. 2020), which may become more common as the climate warms and becomes more variable (Lee 2022).

Climate change is altering the character of winter in historically cold, snow-covered regions (Contosta et al. 2019). Winter air temperatures are rising, snowpacks are thinning, and more precipitation is falling as rain rather than snow. These trends are expected to continue or accelerate (USGCRP 2017, Contosta et al. 2019, Burakowski et al. 2022). Empirical evidence has linked warming Arctic air temperatures to increasing winter variability, including winter weather whiplash events (Cohen et al. 2020). Model projections have suggested that winter weather whiplash will be more frequent in the future, even under optimistic scenarios (Francis et al. 2022) and in regions that have typically experienced winter temperatures below 0 °C (Chen et al. 2021). Some of these winter whiplash events feature anomalously warm conditions that disrupt plant, animal, and human phenology (Tervo 2008, Penczykowski et al. 2017, Ladwig et al. 2019), or atypically wet conditions such as rain-on-snow that threaten water quality and human infrastructure (Li et al. 2019, Seybold et al. 2022). In this study we focused on a single event within a class of events in which winter weather incursions into the fall season created impacts on ecological, social, and economic systems components due to tree damage caused by snow that fell on pre-senescent vegetation (Kane and Finn 2014).

Fig. 4. (A) Variable importance plot of the random forest analysis showing the relative importance of each driver, as determined by the increase in mean squared error to the overall model fit. (B-E) Partial dependence plots showing the marginal effect of each driver on the driver impact (expressed as the ratio of articles to publishing newspapers per county). Snow water equivalent (SWE) is measured in mm, leaf area index (LAI) is unitless, road density is measured in km/km², and income is measured in US$.



Our investigation of the Halloween Nor'easter as an example of winter weather whiplash showed that higher income, higher population density neighborhoods, with more-extensive urban tree canopies were more likely to experience storm impacts. Higher income areas tended to have higher population densities. Well-documented relationships between socioeconomic characteristics, green infrastructure, and urban heat islands may have combined to delay autumn senescence in some locations (Grove et al. 2014, Melaas et al. 2016), such that a greater abundance of trees still in leaf in more densely populated areas that also have greater tree cover posed natural hazards to an early season snowfall. This kind of information may help moderate the effects of future shoulder season snowstorms. For example, utilities might consider land cover or individual species as part of their vegetation management plans (Wanik et al. 2015, D'Amico et al. 2019). Yet, public relations are the most challenging component of roadside vegetation management (e.g., Johnson 2008), and attitudes toward utility vegetation management are influenced by different human dimensions factors and vary across location and scale (Hale and Morzillo 2020, DiFalco and Morzillo 2021, DiFalco et al. 2022). In the autumn of 2011, delayed senescence of species that naturally experience later abscission meant that many beeches and oaks were still in leaf when the Halloween Nor'easter hit. Individuals of these species that were in poor health or showed structural defects may have been more likely to fall on power lines or damage critical infrastructure, such that prioritizing their pruning or removal could have mitigated some storm impacts.

In this study, we relied on publicly available datasets to construct a statistical model of the Halloween Nor'easter that fit within the conceptual framework developed by Casson et al. (2019). Satellite derived LAI used to detect foliage presence at the time of the storm did not provide information about which species were still in leaf. We are not aware of publicly available data across our study area that would allow for species-specific inferences of phenological phase at fine temporal (daily) scales. The National Land Cover Database (NLCD) tree canopy data layer provides national estimates of tree canopy cover, including in urban areas. Yet the five-year update cycle of the NLCD may be too coarse to capture rapidly changing conditions that are a hallmark of weather whiplash (Casson et al. 2019, Lee 2022). As part of determining the human system context in which the storm occurred, we estimated the density of distribution power lines from secondary road density. This was not a perfect representation of the electrical grid (for example, it does not include regional transmission lines), but detailed maps of distribution lines are neither publicly accessible nor in a standardized form that enable regional scale analysis (Arderne et al. 2020). Higher resolution tree cover data and standardized publicly available maps of aboveground distribution lines would enhance the identification of locations at greater risk to winter weather whiplash events like the Halloween Nor'easter.

Studies that evaluate the consequences of extreme events typically consider direct, tangible damages, such as loss of life, insured costs, and federal emergency relief expenditures for which data are readily available (IPCC 2012). Focusing solely on the monetary impacts of extreme events neglects other direct impacts and the complexity of both direct and indirect, intangible social and ecological consequences, such as impacts on disease vectors, impacts on psychological well-being and a sense of security, or impacts on ecosystem services (Spruce et al. 2020). Our newspaper content analysis of newspaper coverage of the storm revealed that although some of the most frequent themes in our dataset such as "power" and "public safety" might have been captured through statistics of outages or accidents, issues related to the themes of "tree damage," "community response," "local impacts," and "other impacts" may have been harder to enumerate because they often occur at the medium and fine scales of neighborhoods or individual property owners (Hasan and Foliente 2015). Lost opportunities for travel, trick-or-treat, and holiday gatherings are examples of intangible impacts of the storm as represented by the "local events" theme. Yet content analysis can also be an imperfect instrument when detecting the impacts of storms like the Halloween Nor'easter. Prior research has demonstrated that media outlets vary in their coverage of extreme weather events, both in the framing of stories and in the inclusion of stakeholder voices, such as based on convenience (Kloster et al. 2019). Thus, journalistic decisions about how to cover a story and whom to interview may affect the occurrence and frequency of themes that represent the human and natural impacts of the storm. The extent and nature of news coverage of storm impacts also influences both the ways affected individuals understand the risk of these events (Conway and Jalali 2017) and also the amount and type of relief aid provided by government agencies (Berlemann and Thomas 2019), and thus may influence the human and natural system context for subsequent storms (Casson et al. 2019).

The Halloween Nor'easter resulted in more than an estimated US$1 billion in economic losses. Despite its magnitude, this statistic underestimates the true consequences of the event because it does not account for indirect, intangible, and direct non-monetary impacts. Our integrated consideration of impacts, based on a coupled human and natural systems framework, revealed greater vulnerabilities to winter weather extreme events than dollar amounts alone, including avoided travel, personal injuries, work and school closures, and disrupted community activities. We characterized both the drivers and the impacts with publicly available data; however, our ability to predict the impacts of the Halloween Nor'easter would likely improve with more granular spatial and temporal data of the natural and human contexts of the event. Although our study focused on a single storm within one region, our analysis demonstrates the necessity of a holistic approach for understanding the meteorological, ecological, and socioeconomic drivers of extreme weather events as a prerequisite to both preventing and mitigating their risks.

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Data Availability:

The data/code that support the findings of this study are openly available in GitHub at https://github.com/creedutsc/2011_noreaster; DOI: https://doi.org/10.5281/zenodo.7323597.

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