Economic losses from extreme weather in the U.S. Gulf Coast region: spatially differential contributions of climate hazard and socioeconomic exposure and vulnerability

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Abstract
Worldwide economic losses from extreme weather events (EWE) have increased over recent decades, with significant geographic heterogeneity in damages. The IPCC defines the risk from EWE as a function of the climate hazard, socioeconomic exposure, and vulnerability. Although these three drivers vary at fine spatial scales, spatial variability largely has been overlooked in assessments of the drivers of economic loss from EWE. Using cluster analysis, we developed a novel socio-climate hazard typology (SCT) that integrates locally defined climate hazard and socioeconomic exposure and social vulnerability typologies. The results identified 838 unique SCT types impacted by EWE across the Gulf Coastal United States during 1981–2010. We regressed the SCT types and their constituent hazard and socioeconomic components against the cumulative economic loss (1981–2010) from EWE for each SCT type. Across the landscape, economic damages of SCT types were determined by unique, spatially explicit combinations of different risk factors, even in explaining the same level of economic loss. For example, multi-billion-dollar damages in the central Gulf Coast and peninsular Florida were explained by different drivers of risk, with damages in the former explained by additive interaction between climate hazard and multiplicative interaction between climate hazard and socioeconomic exposure and vulnerability, and in the latter explained by socioeconomic exposure and vulnerability. These results highlight the need to diagnose additive and multiplicative interactions among drivers of EWE risk in a spatially explicit context.

1. Introduction
Worldwide economic losses from extreme weather/climate events (EWE) have increased over the past decades with significant geographic heterogeneity in devastation [1, 2]. The spatial intersection of a severe climate hazard event with either substantial exposure of socioeconomic assets or acute social vulnerability or both, turn an EWE into a disaster [3, 4]. All three drivers, hazard, exposure and vulnerability, vary spatially and intersect differently in different places. Therefore, the spatial context of these factors is essential for understanding the economic loss from EWE [3–6]. However, this spatial dimension has received little attention in EWE impact research. Existing studies typically apply a temporal trend analysis of economic loss to a given geographic area- most often at country scale [7, 8], normalized by some indicator(s) of socioeconomic exposure and vulnerability. These studies generally conclude that the increase in damage is due to the rise in socioeconomic exposure [7–10]; however, such approaches
may conceal local variations of the three drivers of damage from EWE.

The location dependence of particular climate hazards is well known; certain places experience a specific category of EWE more frequently than others, creating distinct geographical patterns in climate hazards [11, 12]. Likewise, socioeconomic factors such as wealth, population, demography, and lifestyles vary widely over the landscape [13, 14] generating spatial patterns and hot-spots [15, 16] in socioeconomic exposure (defined as the presence of people, economic, social, or cultural and environmental assets on the path of the hazard) [3] and vulnerability (defined as propensity of people, neighborhood and assets in the area of hazard to be adversely affected) [3]. By extracting information contained in the landscape pattern of hazard, exposure, and vulnerability, it should be possible to dissect the landscape into a mosaic of climate hazard types (e.g. hurricane, heatwave, or tornado zones), socioeconomic exposure types (e.g. assets in flood zones exacerbated by the levee effect—increased exposure in flood plains due to false sense of security in the community created by the levee [17, 18], and vulnerability types (e.g. economically challenged neighborhoods). Thus, different combinations of climate hazard, socioeconomic exposure, and vulnerability types at specific locations on the landscape may be integrated to form an operational unit of risk of EWE that we call a socio-climate hazard type. We hypothesize that socio-climate hazard types vary across the landscape such that the drivers of damage, and therefore EWE risk, vary at the local scale within a region. Accordingly, the regional patterns in economic loss from EWE can be explained by regional variation in socio-climate hazard types and provide information on the local contributions of hazard, socioeconomic exposure, and vulnerability. We test this hypothesis in the Gulf-Coastal United States, a hot-spot for EWE and related economic loss.

2. Method

We used insights from high-dimensional statistical modeling [19, 20], a two-step process of statistical analysis for high dimensional data, to develop our methods. In the first step, hierarchical mode association clustering (HMAC) [21] was used for dimensionality reduction to generate landscape typologies of climate hazard and socioeconomic exposure and social vulnerability, which were then combined into an integrated socio-climate hazard typology (SCT) (supplementary information (SI)-I; figure SI-I). This was followed by a regression analysis of economic losses from EWE with the SCT types as the independent variables.

2.1. Landscape typologies

A region experiences climate hazards through meteorological variables such as extreme precipitation, temperatures, and wind gust speeds. We used HMAC to classify meteorological data describing these variables into climate hazard types of a climate hazard typology (CHT). As many EWE exhibit a seasonal cycle and interannual to multidecadal variability [22], 30 years (1981–2010) monthly, seasonal and annual means, standard deviations, maxima, minima and ranges of daily minimum temperature, maximum temperature, and precipitation from the DAYMET dataset [23] for the region were used in the clustering (typing). The lack of uniform high-resolution wind speed data for the study area prevented the use of wind speed as a variable. HMAC generates a hierarchy of clusters; each level in the hierarchy represents a typology and clusters of similarity in that level are the types in that typology. Once the CHT hierarchy was generated, a fixed-effect regression model for types against the frequencies of EWE (hurricane, tornado, hailstorm, wind, and flood) weighted by their magnitude (FWM) calculated from the hurricane, tornado, hailstorm, wind, and flood event datasets (data sources and details of analysis are in SI-II-1 (stacks.iop.org/ERL/15/074038/mmedia)) was evaluated for the presence of robust signals of climate hazards in each level in the CHT hierarchy. The result showed that CHT fixed-effect models produced a minimum adjusted-$R^2$ value of 0.83 across different climate hazard events. We chose the level with the greatest explanatory power, largest adjusted-$R^2$, the strongest signal of climate hazard, as the CHT for the region (SI-II; figure SI-II-1).

Socioeconomic exposure and social vulnerability are largely the result of socioeconomic development pathways and societal conditions [3]. Socioeconomic exposure and social vulnerability in a region are driven by a common set of socioeconomic, demographic and institutional variables. Consequently, the same variables can contribute to both exposure and vulnerability and there is no practical approach to identify the range of these variables that contributes only to exposure or vulnerability without detailed information about specific cases and contexts. For example, wealth is at the same time a contributor to high exposure and low vulnerability and an extant partitioning of wealth levels that contribute only to exposure or vulnerability is not feasible. Hence, using HMAC, we characterized the joint socioeconomic exposure and vulnerability of the region with a combined socioeconomic exposure and vulnerability typology (SEVT). We used county-specific 30 years (1981–2010) means and standard deviations of population and other demographic variables along with unemployment, education, household income, road connectivity, social capital variables, percent impervious surface, infrastructure intensity and USDA Rural-Urban code in the clustering (details of data and their sources are given in SI-II-2). We found, housing density, a typical variable used to represent socioeconomic exposure, is highly correlated with population density.
2.3. Statistical modeling
Statistical modeling was used to explain regional cumulative economic loss from EWE. First, a fixed effect model (model 1; equation (1)) with cumulative economic losses from EWE as the dependent variable and SCT types as the predictors was used to identify the SCT types statistically significant in determining economic loss:

$$\hat{Y}_i = \alpha + \beta_i \text{SCT}_i$$  \hspace{1cm}(1)$$

where $\hat{Y}_i$ is the predicted cumulative economic losses from EWE in SCT type $i$, $\alpha$ is the intercept, which represents the contribution of statistically non-significant SCT types to the regional economic loss or average contribution from all SCT types, and $\beta_i$ is the regression coefficient for SCT type $i$. Model 1 differentiates the total SCT types over the region into those SCT types significantly (statistically significant $\beta_i$) contributing to the regional economic loss and SCT types not significantly contributing to the regional economic loss. The fixed-effect controls for the average differences across SCT types and quantifies how a specific SCT type is different from all other SCT types.

After identifying the SCT types that significantly influence the regional economic loss from equation (1), a second SCT-components model (model 2, equation (2)) was used to decompose contributions from the significant SCT types into their component significant types and/or their combinations (i.e. CHT or SEVT type alone or their multiplicative and additive interactions):

$$\hat{Y}_i = \alpha + K_i \times (\beta_{ic} \text{CHT}_{ic} + \gamma_{is} \text{SEVT}_{is} + \delta_{ic} \text{SEVT}_{is} \times \text{CHT}_{ic})$$ \hspace{1cm}(2)$$

where again $\hat{Y}_i$ is the predicted cumulative economic losses from EWE in SCT type $i$, which is a combination of a CHT type $c$ and a SEVT type. The intercept $\alpha$ represents the contribution of statistically non-significant SCT types or the average contribution from all SCT types towards the regional economic loss. The $\beta_{ic}$, $\gamma_{is}$ and $\delta_{ic}$ are the regression coefficients of CHT$_{ic}$, SEVT$_{is}$ and their multiplicative interactions respectively. The term CHT$_{ic}$ identifies the CHT type $c$ that uniquely combined with SEVT types defines SCT type $i$; similarly, for SEVT$_{is}$. We used dummy variable regression to estimate model 2, where a dummy variable for $K_i$ was used for isolating the significant SCT types from the non-significant SCT types without changing the sample.
Figure 1. Cumulative economic losses (1981–2010) from extreme weather events (EWE) for the Gulf Coastal United States encompassed by the region’s SCT.

size; $K_i = 1$ for significant SCT types and 0 otherwise. The terms $CHT_{ic}$ and $SEVT_{is}$ of the SCT$_i$ in model 2 were also defined as dummy variables. For example, if a SCT type contained a specific CHT type, that CHT type was assigned a value of 1 otherwise it received a value of 0; likewise, for the SEVT types. We used step-wise regression with a $p$-value of 0.05 as the parameter selection criteria for model 1 and 2.

We used significant regression coefficients of CHT type ($\beta_{ic}$), SEVT type ($\gamma_{is}$) and their multiplicative interaction ($\delta_{ics}$) to estimate the contribution of climate hazard, socioeconomic exposure and vulnerability and their multiplicative interaction towards economic loss from EWE. First, we separately summed $\beta_{ic}$, $\gamma_{is}$, and $\delta_{ics}$ over the significant SCT types to calculate the aggregated contributions of CHT, SEVT and their interaction to regional economic loss. Contributions from all possible combinations of significant CHT type, SEVT type and SEVT $\times$ CHT types in SCT types over the region were then separately calculated. This was done by grouping the significant SCT types in equation (2) into the seven possible combinations of how significant CHT types, SEVT type and SEVT $\times$ CHT types might appear in a SCT: CHT type alone, SEVT type alone, and their multiplicative interaction alone (equations (3)–(5)) along with four groups of SCT types with additive interactions between more than one significant type (equations (6)–(9)). For example, in equation (7), both CHT type and CHT $\times$ SEVT types significantly contribute to economic loss of corresponding SCT type in an additive interaction of CHT type and CHT $\times$ SEVT types.

1. A SCT type with significant CHT type

$$\hat{Y}_i = \alpha + \beta_{ic}CHT_{ic}$$

2. A SCT type with significant SEVT type

$$\hat{Y}_i = \alpha + \gamma_{is}SEVT_{is}$$

3. A SCT type with significant CHT $\times$ SEVT types

$$\hat{Y}_i = \alpha + \delta_{ics}SEVT_{is} \times CHT_{ic}$$

4. A SCT type with both CHT type and SEVT types significant

$$\hat{Y}_i = \alpha + \beta_{ic}CHT_{ic} + \gamma_{is}SEVT_{is}$$

5. A SCT type with both CHT type and CHT $\times$ SEVT types significant

$$\hat{Y}_i = \alpha + \beta_{ic}CHT_{ic} + \delta_{ics}SEVT_{is} \times CHT_{ic}$$

6. A SCT type with both SEVT type and CHT $\times$ SEVT types significant

$$\hat{Y}_i = \alpha + \gamma_{is}SEVT_{is} + \delta_{ics}SEVT_{is} \times CHT_{ic}$$

7. A SCT type with CHT type, SEVT type and CHT $\times$ SEVT types significant

$$\hat{Y}_i = \alpha + \beta_{ic}CHT_{ic} + \gamma_{is}SEVT_{is} + \delta_{ics}SEVT_{is} \times CHT_{ic}$$

3. Results and discussion

3.1. Climate hazard, socioeconomic exposure and vulnerability and socio-climate hazard typologies

The 643 counties in the region were dissected into 122 unique CHT types (figure 2(A)) and 164 SEVT
types (figure 2(B)). The spatial intersection of CHT and SEVT types generated 2241 unique SCT types (figure 2(C)), of which 838 SCT types were impacted by EWE (figure 2(D)). The creation of many unique SCT types highlights the geographic heterogeneity in risk of EWE over the region arising from spatial variation in hazard and socioeconomic exposure and vulnerability captured in CHT and SEVT types, respectively.

3.2. Influence of SCT on regional economic loss

The SCT fixed-effect model (model 1, equation (1)) explained 92% of the variation in economic loss from EWE in the region (SI-II-4; figure SI-II-4). Only 12% of SCT types were statistically significant (SI-II-5; figure SI-II-5) but contributed 82.61% ($142.03B) of the regional economic loss. The remaining non-significant SCT types (88%) contributed a combined $29.89B (summation of $ in equation 1 over non-significant SCT types). A comparison of predicted and reported economic loss using a regression showed that losses predicted by the SCT fixed-effect model are statistically not different from the reported losses (see SI-III-for details). Separate CHT fixed-effect and SEVT fixed-effect models had adjusted $^{2}$ values of 0.42 and 0.28 respectively, less than that of the SCT fixed-effect model. The result indicates that the SCT fixed-effect model outperformed the CM model. The $^{2}$ value of the CM model was 0.19 compared to 0.92 for the SCT model, and RMSE for the SCT model-1 was 21.16% of RMSE for the CM approach (see SI-III-2 for details). As an SCT type is a composite of two contributing types, a CHT type and a SEVT type, the SCT fixed-effect model in effect portrays the interaction between climate hazard and socioeconomic exposure and vulnerability over the landscape. Therefore, the effectiveness of the SCT fixed-effect model for predicting spatially explicit economic losses from EWE signifies the importance of the local spatial context of risk, the spatially explicit interaction of climate hazard and socioeconomic exposure and vulnerability.

3.3. Estimates of CHT and SEVT contribution to regional economic loss

We found that the SEVT explained $56.46B (39.75%) of regional losses while the CHT was responsible for $31.76B (22.36%) and the multiplicative interaction of the CHT and SEVT (the CHT $\times$ SEVT) contributed $53.81B (37.88%). The dominance of the SEVT over CHT is in line with the current understanding of impact analysis research in which temporal variation in socioeconomic exposure drives economic loss from EWE over time rather than changes in climate hazard [7–10]. But in a spatial context, the relative contribution of each type is not always dichotomous or separable. A sizable share of regional economic loss (37.88%), rivalling the contribution from SEVT, is explained by the multiplicative interaction of SEVT and CHT types. Because a coincidence of hazard and
socioeconomic exposure and vulnerability is essential for economic damage from EWE, one might expect the CHT $\times$ SEVT interaction to be dominant in explaining regional economic loss. Its contribution is large but not dominant.

The contributions of CHT, SEVT, and their CHT $\times$ SEVT interaction exhibited distinct regional patterns (figures 3(A)–(C)). The influence of interaction of CHT type $\times$ SEVT type was, as expected, widespread across the region (figure 3(A)). In contrast, the influence of CHT type and SEVT type was differentially confined to specific geographic areas: CHT types in the central Gulf Coast (southern Louisiana and Mississippi) (figure 3(B)) and SEVT types in peninsular Florida (figure 3(C)) and. The prevalence of interaction of CHT type $\times$ SEVT type as the prime driver of economic loss across the region again demonstrates the universality of the IPCC conceptualization of risk from EWE as an intersection of climate hazard, socioeconomic exposure and vulnerability. Conversely, the occurrence of significant SEVT and CHT types over specific areas shows that these factors may be differentially prevalent.

Most of the area where damages were explained by SCT types with significant CHT type (figure 3(B)), specifically in Louisiana and Mississippi, coincided with the area impacted by Hurricane Katrina, the largest single disaster in our data set. To test whether this single event biases CHT-prevalence as the driver of EWE damage and the observed spatial pattern, we re-calculated economic loss excluding the damages from hurricane Katrina for impacted counties in Louisiana and Mississippi and re-estimated equation (2). As influence of Hurricane Katrina can be displayed through CHY type or CHT type $\times$ SEVT type, we examined significance of CHT type and CHT type $\times$ SEVT type between these two models to understand biases created by Hurricane Katrina. The results revealed that the spatial pattern of predominance of CHT type in the affected region persists without the damages from hurricane Katrina (figure SI-IV-1). We further found that the interaction of CHT type and SEVT type in the region was significant in the without-Hurricane-Katrina model. Therefore, the influence of CHT type on economic loss is robust and determined by locally defined factors rather than an outcome of a single event like Hurricane Katrina (details are in SI-IV-2).

The overlapping areas of significant CHT types, SEVT types, and CHT type $\times$ SEVT type observed in certain places (figures 3(A)–(C)) indicates the presence of additive interaction between significant types in specific spatial contexts (equations (6)–(9)). Among all possible combinations, SCT types with additively interacting CHT and SEVT $\times$ CHT (equation (7)) were responsible for the largest share ($52B$) of the total economic loss (figure 4(A)). SCT types with significant SEVT $\times$ CHT (equation (5)) contributed an additional $18B$ and those with CHT type alone (equation (3)) contributed another $14B$ (figure 4(A)). Hence, damages ($84B, 59\%$) were strongly dominated by SCT types involving some type of significant CHT contribution. Recall that when we decomposed the total economic loss into the three major groups without considering additive contributions, SEVT dominated total economic loss. When additive combinations are considered the role of hazard (CHT) is more evident. These results demonstrate the need to consider additive interactions in analyzing the risk of economic loss from EWE. Nevertheless, the contribution of socioeconomic exposure and vulnerability is still visible. First, the second largest contribution ($26B$) came from SCT types with a significant SEVT type alone (combination 2, equation (4)). Second, note that the contribution from CHT in combination 4 (equation (6)) and SEVT $\times$ CHT in combination 6 (equation (8)), both with significant SEVT, are marginal (figure 4(A)).

There was a distinct spatial pattern in the contribution of drivers of economic loss in SCT types, with two contrasting areas that coincide with the greatest economic losses in the region (figures 3(B), (C) and 4(B)). Note in figure 4(B) the blue area surrounding the New Orleans area in which the contribution of CHT types alone is significant and the red area surrounding the central portion of peninsular Florida where the contribution of SEVT types alone is significant. In both cases, multiplicative CHT $\times$ SEVT type interaction is significant (figures 3(A) and 4(A)). However, the magnitude of the contribution of the CHT $\times$ SEVT interaction (in combination 6; equation (6)) in Florida is very marginal (note column 6 of figure 4(C)), whereas the CHT $\times$ SEVT interaction (in combination 5, equation (7)) contributed two-thirds of the explained economic loss in the New Orleans area (note column 5 of figure 4(B)). Therefore, it is evident that the comparably high losses in these two areas were explained by different drivers of risk. Interestingly in the New Orleans area the contribution from socioeconomic exposure and vulnerability was expressed only in the interaction with climate hazard while in peninsular Florida the contribution from socioeconomic exposure and vulnerability generally dominated. Thus, different combinations of climate hazard, socioeconomic exposure and vulnerability and their interactions can determine similar level of economic loss from EWE; socioeconomic exposure and vulnerability dominate losses in some locations, but not everywhere.

As noted, the CHT $\times$ SEVT term contributed marginally to economic losses in Florida but dominantly contributed to losses in the New Orleans area. We hypothesized this contrast was due to differences in the nature of the climate-socioeconomic interactions between the two subregions. To test this, we expanded the SCT model 2 (equation (2) by adding
Figure 3. Spatial patterns of (A) SCT types with significant SEVT × CHT types; (B) SCT types with significant CHT types; (C) SCT types with significant SEVT types.
variables to specifically quantify climate hazard and socioeconomic exposure and social vulnerability together with their interactions, teasing apart the CHT type × SEVT type interaction into contributing factors. In the event that SCT type had significant contribution of CHT type × SEVT type in addition to the individual significance of CHT or SEVT (combinations 5 and 6 above) in SCT model 2, we replaced the value of 1 for a dummy variable for the CHT type × SEVT type interaction with value of FWM to examine the contribution of climate hazard. Similarly, the CHT type × SEVT type dummy value of 1 was replaced with PFW and with SoVI to examine, respectively, the contribution of socioeconomic exposure and the contribution of social vulnerability. Additionally, we examined the interaction between FWM, PFW and SoVI. We found that the influence of climate hazard, socioeconomic exposure and social vulnerability in the CHT type × SEVT type interaction was indeed different between the two subregions. In the case of the central Gulf Coast, socioeconomic exposure (PFW) and the interaction of climate hazard and social vulnerability (FWM × SoVI) define the interaction of CHT type × SEVT type. In contrast, climate hazard (FWM) plus social vulnerability (SoVI) characterize the interaction of CHT type × SEVT type in Florida. These differences in the CHT type × SEVT type interaction likely explain the differential contribution of CHT × SEVT in the two areas.

Figure 4. (A) Decomposition of regional economic loss into all combinations of CHT and SEVT types and their multiplicative CHT × SEVT interactions. (B) The spatial pattern of different combinations of significant CHT, SEVT types and their CHT × SEVT interactions.
All data are to some degree uncertain, and that uncertainty will propagate through any analyses. Therefore, propagation of uncertainty in input data through the clustering algorithm could yield different SCT types. We used the best available data for the study area as input to the cluster analysis and these data have historically been tested for their robustness while used in shaping several regional policies. We therefore do not consider alternative datasets as a relevant source of uncertainty. Uncertainties in the datasets we did use is generally not available, but in any case, we believe it unlikely that data uncertainties of that nature would substantially alter the findings of our study. We avoided the uncertainty that might arise from selecting the number of clusters in a k-means clustering by using an objective criterion for choosing the level of the resulting hierarchy for use as the typology. An alternative criterion and choice of typology might yield different SCT typologies, but we believe our chosen approach is most appropriate.

Further, we did examine several sources of uncertainty arising from our analyses because the analytical uncertainty is likely to exceed any data uncertainty in SCT types. We found that the model explaining economic damages as a function of SCT types was robust against sample size and composition (2-folded cross-validation), level of aggregation (SCT model for the county), an alternative source of economic loss data (i.e. preliminary damage assessment reported by Federal Emergency Management Agency [20]), alternate ways of distributing county loss over SCT types, quantiles of economic loss values, any bias from Hurricane Katrina and the possibility of false-positives (see SI-III-2–9 for details). The cross-validation, in particular, indicates that our resulting model would be robust to variation in the SCT types. Moreover, our statistical approach to relating landscape types to outcomes rather than a deterministic model accommodates a reasonable amount of uncertainty.

4. Conclusions

We have demonstrated that the landscape typology perspective [20] is able to extract information from spatial heterogeneity in damages from EWE. The contribution of hazard, socioeconomic exposure and vulnerability to risk from EWE, or the realized risk in the form of damages, is complex and highly multidimensional. Each of the three components is a combination of many different variables and drivers that interact within and among the components. The typology approach reduces this dimensionality to more manageable levels while retaining the information inherent in these multi-dimensional interactions. Even in reduced dimensional space, the CHT and SEVT retained robust signals of climate hazard and socioeconomic exposure and vulnerability respectively. We successfully applied the integrated SCT as an operational unit of risk to spatialize IPCC’s risk conceptualization for EWE and established a spatially-explicit statistical relationship between economic loss and the SCT types and their components. Hence, our typology framing allows a spatially-explicit and functional understanding of spatial drivers of risk from EWE. Although the typology approach is inherently integrative, it is possible to disentangle the interactions between climate hazard and socioeconomic exposure and vulnerability and their contribution to risk and economic loss.

As noted in the introduction, analyses of the temporal dimension of economic loss from EWE have generally concluded that the historical increase in damages in the United States and worldwide is largely a consequence of an increase in socioeconomic exposure [7–10]. Here we have demonstrated that spatial patterns in economic loss from EWE contain information relevant to that discussion. We have found, for example, that while damage from EWE is clearly a consequence of some combination of hazard, exposure and vulnerability, the nature of the influence of drivers and their interactions can differ spatially, even in explaining the same level of economic loss. For example, large damages in the central Gulf Coast and peninsular Florida were explained by different combinations of hazard, socioeconomic exposure and social vulnerability. Why this should be so is less clear. It may be that in areas like the central Gulf Coast where climate hazards are endemic and diverse [22], climate hazards impart a strong signal on damages, whereas in areas like peninsular Florida where climate hazards are more singular and episodic (i.e. hurricanes) [12, 22] the signal of exposure and vulnerability is expressed over that of climate hazard. On the other hand, the differences may reflect differences in socioeconomic exposure and social vulnerability experienced by these two areas. In Preston [24], temporal changes in socioeconomic exposure in Florida were due to an increase in population, while the increase in wealth drove the changes in socioeconomic exposure in the central Gulf Coast [24]. Similarly, in Cutter et al [25] there was a distinct geographic disparity in social vulnerability experienced by these two areas with high social vulnerability in the central Gulf Coast, while Florida exhibited moderate social vulnerability [25]. These local differences may influence the role of socioeconomic exposure and vulnerability in determining economic losses from EWE for these two areas; socioeconomic exposure and vulnerability dominated the economic losses from EWE in Florida, while in the central Gulf Coast, the role of socioeconomic exposure and vulnerability is limited to the interaction between climate hazard and socioeconomic exposure and vulnerability.
As demonstrated in Nair et al [20], it is possible to decompose our landscape types (e.g. CHT type) into contributing factors. That study, using a landscape typology to diagnose spatial variations in agricultural yield, found that the types of the contributing socioeconomic typology were influenced predominately by farm size, education, total factor productivity, and household median income. Thus the interpretation that those factors were deterministic of regional variations in crop yield [20]. While beyond the scope of the current study, a similar decomposition of CHT and SEVT types could be applied and provide further insight into determinants of economic loss from EWE in the region.

Our study highlights the need for diagnosing all components of risk simultaneously, especially their additive and multiplicative interactions, and in a spatial context. The assumptions inherent in the common approach to temporal analyses of damage from EWE in which quantitative damages are normalized by some metric of exposure, either with population or with wealth, seeking to isolate a signal from change in hazard, may need reconsideration [28]. Proportionality is the central assumption in normalization [7, 8, 28]. Our demonstration of the presence of additive combinations among the drivers of the economic loss nullifies that assumption. Further investigation on presence of additive interaction between hazard and socioeconomic exposure on temporal dimension is needed. A temporal analysis of economic loss from EWE that accounts for the spatial context of the drivers and their complex interactions may show a climate hazard signal in the economic loss in some sub-regions, while not in others, a distinction that may be lost in temporal trend analysis of economic loss normalized by proxies of socioeconomic exposure and vulnerability.

The lack of availability of high-resolution data is the major limitation for replicating the approach in other areas. But as described in SI-V, data limitation is rapidly being alleviated. Additionally, the study lacks temporal dynamics: temporal dynamics in the SCT, how do types and spatial distributions change over time, and temporal dynamics in the relationship between SCT types and economic damages. The temporal evolution of landscape types and their relationship with changes in economic losses might provide new insights, which can be addressed in future research.

Finally, our use of landscape typology in analyzing economic loss from EWE has illustrated that the drivers of risk explaining those losses are spatially heterogeneous. The mix of responsible drivers may be very localized. This approach to the diagnosis of risk and economic loss from EWE could be used to prioritize consideration of components of risk by communities and regional authorities considering risk management strategies and planning for resilience to climate change and EWE. We conclude that acknowledging and understanding the role of spatial specificity in drivers of economic losses and their interactions can inform both historical diagnoses of changes in economic loss from EWE and future planning.

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Data availability statement

The non-proprietary data that support the findings of this study are available from the corresponding author upon reasonable request.

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