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Nighttime light data reveal lack of full recovery after hurricanes in Southern US

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Abstract
As the climate warms, many areas of the world are experiencing more frequent and extreme weather events. Hurricanes carry some of the costliest short-term socioeconomic repercussions via economic losses and people displaced. There is, however, little quantitative evidence regarding medium- to long-term effects, nor factors moderating recovery. Here we show that areas affected by hurricanes of category 4 or 5 in the southern US between 2014 and 2020 generally do not demonstrate full recovery in the longer term. Utilizing Visible Infrared Imaging Radiometer Suite nighttime light (NTL) data as a proxy for economic activity and population density, we build a timeline of recovery via NTL radiance levels. We exploit the difference in the eligibility for aid from the Federal Emergency Management Agency (FEMA) to apply a quasi-experimental method to identify changes in NTL radiance attributable to hurricanes. We find that after three years, affected areas demonstrate a reduction in NTL radiance levels of between 2% and 14% compared to the pre-disaster period. Combining these results with machine learning techniques, we are able to investigate those factors that contribute to recovery. We find counties demonstrating smaller reductions in NTL radiance levels in the months following the hurricane are buoyed by the amount of FEMA aid received, but that this aid does not foster a longer-term return to normal radiance levels. Investigating areas receiving FEMA aid at the household and individual level, we find age and employment are more important than other demographic factors in determining hurricane recovery over time. These findings suggest that aid may be more important in motivating short-term recovery for public entities than for individuals but is not sufficient to guarantee complete recovery in the longer term.

1. Introduction

Weather extremes can affect ecological and socioeconomic systems profoundly [1–4]. Hurricanes are among the costliest natural disasters in the United States. Between 2005 and 2020, the total estimated damages from tropical cyclones amounted to $595 billion; 43% of that total occurred since 2015 [5]. With continued climate change, such events are becoming more intense and frequent in many parts of the world. It is therefore increasingly important to understand the consequences of these events, and our ability to recover from them, as well as possible linkages to adaptation behaviors such as migration.

Studies on the economic consequences of hurricanes have already suggested the temporal complexity of recovery patterns [6] especially in the context of climate change-adaptive behaviors [7]. There is evidence that out-migration from hurricane-prone areas may already constrain recovery in areas affected by large hurricanes [8]. Most studies have investigated the effects of one or two hurricanes in isolation and over short time lines, often spanning only months, and conclusions of empirical studies on longer-term

effects are ambiguous. Some find that disaster affected areas in both rich and poor countries do not return to pre-disaster income levels even 20 years post-disaster [9] whereas others find no long-lasting significant effects using nighttime light intensity [10–13] or even a rebound in brightness after a disaster [14].

The determinants of post-disaster recovery also remain poorly understood, despite their potential to inform disaster aid policy, motivate recovery, and enable better quantification of the costs of climate change. Studies have pinpointed emergency aid as a mitigator to out-migration from disaster-affected areas [15] and its slow dispersal as an impediment to recovery [16]. For developed countries, post-disaster migration has been shown to be complex, with the variance in migration across affected areas often explained by the presence of disadvantaged populations, lower overall ex-ante levels of development, or rural or urban status [17, 18]. Federal Emergency Management Agency (FEMA) aid may also act as a moderator of post-disaster migration for low-income households [19]. Others find that factors of social vulnerability are less important in motivating migration than the severity of the disaster [9, 20].

We aim to fill both these gaps by investigating the evolution of hurricane response dynamics over time and identifying the comparative importance of socioeconomic, demographic, and aid-related factors that could drive adaptation responses. To this end, we build a combined data set matching indicators on the reception of FEMA post-disaster aid to monthly geolocated visible infrared imaging radiometer suite day/night band nighttime light (VIIRS NTL) data, urbanization data from the National Center for Health Statistics, and county-level demographic and socioeconomic data from the US Census Bureau and Bureau of Economic Analysis for all category 4 and 5 hurricanes which made landfall in the United States between 2014 and 2020 (see data & methods section of the supplementary materials for detail).

VIIRS NTL data may offer crucial insights into storm recovery dynamics across time and socioeconomic conditions, given their highly granular temporal and geographic resolution and significant correlations to both gross domestic product [21–23] and population density [24–27] as well as their ability to effectively capture patterns of urbanization around the world [28, 29]. These data have previously been used to study time trends of light recovery correlated with one or two hurricanes, or over short time scales [25, 30–34].

Here, we study the effects of many hurricanes at once on a monthly basis, and for the oldest storms, over longer time spans than previously studied. We further build on correlative, time-series based work by employing a quasi-experimental method, a difference-in-differences (DiD) model, to estimate the plausibly causal effects of hurricanes on changes

in night light intensity. We then apply tree-based machine learning models in conjunction with the Shapley Additive explanations algorithm (SHAP) to identify those variables most important in explaining differences in hurricane responses across different counties. SHAP is already widely used in combination with tree methodologies to explain endogenous trends in climate-related human behavior [35, 36]. It has been found to produce local feature importance estimations that are both generalizable to the global model, and well in line with human intuition [37, 38].

2. Method overview

2.1. Data
We build our main dataset by matching monthly VIIRS NTL radiance data [39] and data on Individual and Publicly available FEMA post-hurricane disaster assistance at the county level [40] for seven hurricanes [41]. The FEMA disaster assistance data identifies those counties in which individuals and households (referred to as Individual Aid hereafter), public entities and nonprofits, or both groups (referred to as Combined Aid hereafter), were eligible for disaster-related relief aid from FEMA. We use this information to identify counties affected by each hurricane (the 'treatment' group for that hurricane) and unaffected counties in the same state (the 'control'). We define two treatment groups, evaluated separately, based on the type of FEMA aid for which they were eligible: Individual or Combined aid. Maps of the areas receiving each type of aid as well as unaffected areas can be found in supplementary figures 1–7.

For further controls, supplementary data on rural and urban areas [42], as well as geographic county boundaries [43], and dollar amounts of total aid provided by FEMA, are added to these data [40]. Last, we include socioeconomic [44] and demographic data [45] on the county level. For details on each dataset, please see supplementary materials: Data & Methods, along with a conceptual overview of the methodology employed in supplementary figure 8.

2.2. Empirical strategy
In order to gain insight into the potential *causal* effects of hurricanes on NTL intensity changes, we employ a DiD methodology. This method first assesses the difference in the level of nightlight radiance between the pre-hurricane period and the post-hurricane period for both the group of counties affected and the group of counties unaffected by the hurricane, separately (first difference). It then subtracts the average change in NTL levels in the treatment group from that of the control group (second difference). If the change in radiance after the storm was only assessed for counties affected by the hurricane, the estimation may be biased due to the effect of trends and events other than the hurricane on the

level of NTL. The second difference removes these biases. Given that the same time period is being compared in both the treatment and control groups, the data does not need to be preprocessed to remove seasonality, as seasonal trends affect both the treatment and control. Similarly, if the difference in NTL radiance between treated and untreated counties was only assessed for the post-hurricane period, there could be biases due to already existing differences between the two groups of counties. The first difference removes those biases. Taken together, the two differences yield a suitable counterfactual, thus enabling the estimation of a plausibly causal effect of a hurricane on the level of radiance in the affected counties.

For each hurricane, we run two DiD models for each storm, one for each treatment variable based on the type of FEMA aid received. For all storms, the entire timeline available is used, meaning earlier storms have fewer months of 'pre-storm' data entries (with the minimum being 32 months for the earliest storm) and later storms have fewer post-storm data entries (with a minimum of 16 months). As we assess recovery over time, we shorten the timeline of data month by month, relative to when the storm hit.

The difference-in-differences specification follows:

$$Y_{ct} = \beta_0 + \beta_1(\text{post} \times \text{treatment})_{ct} + \beta_2\text{post}_t \\ + \beta_3\text{treatment}_c + \alpha X_c + \varepsilon_{ct};$$

where Y_{ct} is the log of the NTL radiance level in county c at time t (with t being a month in a year). post_t is a binary variable, taking the value of 1 if t falls in the period after the hurricane (post-period) and 0 if it falls in the period before the storm. The binary treatment_c indicates whether county c is in the treatment group ($=1$) or in the control group ($=0$). Accordingly, the interaction term, $(\text{post} \times \text{treatment})_{ct}$ takes the value 1 only if the outcome was observed in the treatment group and in the post period, and is zero in all other cases. The difference-in-difference effect, β_1, is our coefficient of interest, denoting by how much the difference in NTL radiance between the treatment and control group changed after the hurricane. It can hence be interpreted as the percent change in NTL radiance in the affected counties after the hurricane over the whole post-disaster period up to time t. X_c is a vector of economic and demographic controls on the county level c, and ε_{ct} is the idiosyncratic error term on the month and county level. Running the DiD model for different post-disaster time horizons provides us with a recovery time series indicating the plausibly causal effect of a storm on NTL radiance for different time periods.

Our identification strategy rests on the validity of the 'common trends' assumption: in the absence of the hurricane, the treatment and control areas would have followed the same trend in nighttime

Table 1. Interpretation of the results of the 'leave-one-out' DiD method. The leftmost column of table 1 indicates the sign of the estimation resultant from the DiD model. The middle column indicates the sign of difference between that estimation (here, 'average change') and the estimation resultant from the DiD model when that county is omitted. The rightmost column provides our interpretation of these signs for the county omitted.

Average change in radiance	(Average change)— (change when county omitted)	Interpretation for county being left out
−	−	More radiance reduction than average
−	+	Less radiance reduction than average ('*better off*')
+	−	Less radiance increase than average
+	+	More radiance increase than average

light radiance [46]. To assess this assertion, we compare NTL radiance trends in both groups prior to the hurricane. We find the treatment and control follow a common trend, suggesting that the divergence in light we see post-hurricane is indeed due to the hurricane. Graphical representations for each hurricane are found in supplementary figures 9–15.

2.3. Identifying county-level effects using a leave-one-out method

The DiD methodology requires an aggregate comparison between the treatment and control groups, and the pre- and post-storm periods. The use of this counterfactual between treatment and control ensures that trends affecting both groups are differenced out, strengthening the inference of causality. As a consequence, changes in NTL radiance can only be assessed as an average across all counties and not at the individual county level. In order to gain insights into a hurricane's effects at the county level and possible differences between counties, we combine the DiD method with a 'leave-one-out' approach. Specifically, we iteratively re-estimate the DiD model, excluding one county at a time, for the full time period after the storm available for each storm. After subtracting these estimations from the DiD estimation with all counties included, we are left with the difference due to each county's exemption from the model (measured in percentage points). For clarity, we have included the possible outcomes from comparing two estimations and their interpretations in table 1. We are principally interested in those counties that demonstrated a smaller reduction in lights than the overall reduction in lights for that storm, which we term 'better off'.

2.4. Specifying motivators of differential overall response to hurricanes via SHAP

Focusing on those hurricanes where we find an overall reduction in NTL due to the storm, we aim to identify those factors most important in explaining differences in hurricane recovery across counties, i.e. whether a county experienced more or less negative change in light after a hurricane (examining the whole time period). To this end, we train a tree-based machine learning classifier to predict the likelihood of each county having demonstrated a smaller reduction in light than the overall reduction in light for that storm (being 'better off'), based on a variety of socioeconomic, demographic, and FEMA-aid based factors at four time stages: three months, six months, and one year after the storm, as well as for the full available timeline. We train three tree-based machine learning classification models first to predict the likelihood of a county being better off than the average county hit by the same hurricane: Random Forest, Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine. The model is trained on 70% of the data and tested on the remaining 30%. For each time period and treatment variable, we employ the best performing algorithm based on predictive accuracy. Supplementary table 1 gives a description of all variables, supplementary table 2 provides prediction accuracy for each algorithm, and the Data & Methods section of the supplementary material describes the classifiers in more detail. We back out the importance of each variable in predicting the outcome via the SHAP feature importance analysis methodology. Using the trained model, SHAP assigns a value of importance to each feature in the model, associated with a particular prediction value in the test set. For each of these predicted values, the contribution of each feature to that prediction is calculated, based on the magnitude of that feature's contribution alone and in combination with other features. We average these local feature importance values to derive a globally generalizable importance score for each feature.

3. Results

3.1. Lack of full recovery three years after storms

Using the DiD specification, we compute a storm's average effect on NTL for each hurricane. Separate models are constructed for the two treatment variables, and include NTL values for all time steps (months) available after the storm.

All storms for which there is three years or more of data after the storm demonstrate negative changes in light due to the storm (table 2). As a general trend, hurricanes that occurred earlier (and for which a longer timeline is therefore available) exhibit stronger reductions in NTL at lower p-values, the latter of which is likely due to the increase in data points in the post-hurricane period. For hurricanes with

statistically significant negative effects in areas receiving combined aid, we also see a decrease in NTL intensity associated with being in areas receiving individual-level aid alone.

These results suggest a lack of full recovery over two dimensions: over time, and geographically, in counties affected by the storm. We break down our analysis by time, re-estimating the DiD model while limiting the period after the storm month by month during the subsequent two years. Hence, we are able to compare the short-term changes in light month by month between storms, regardless of when the storm occurred.

For the oldest storms, Hermine, Matthew, Harvey, and Irma in the individual-aid case, the overall effect remains negative over time, for both types of treatment variables (figure 1). This is even more remarkable as the initial effect after a few months was an increase in light for Hermine and Matthew in the case of combined aid, and for Matthew also in the case of individual aid. For Michael, we find a strong decrease in radiance levels in the months after the storms hit with radiance levels then returning to pre-storm levels after about a year. For the most recent storms the overall effect is positive, though the time frame is likely too short to draw robust conclusions as also reflected by the respective p-values for Combined Aid (table 2). In both cases, the post-period of the hurricane is defined as all months following the storm. We find a similar lack of recovery when the post-period is defined as just the respective month, excluding the months between the storm and the month being evaluated, as shown in supplementary figure 16.
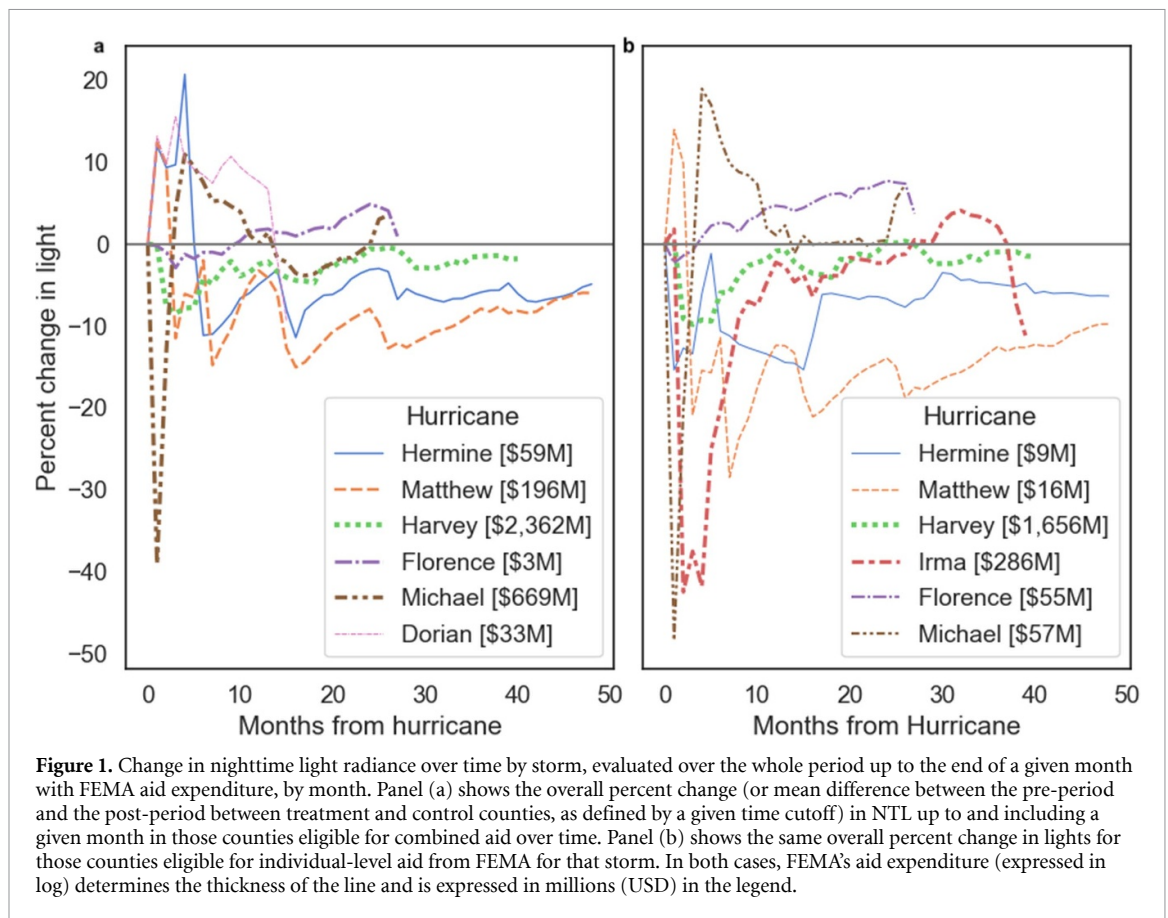
3.2. Hurricane response differs across affected counties

The previous two analyses suggest that at longer time frames, areas affected by hurricanes generally do not return to their previous levels of radiance. These results are in the geographic aggregate, however, and we may therefore miss any potential disparate geographic effects. Employing a 'leave-one-out' approach where the DiD model is re-estimated for all but one county, we are able to isolate the contribution of that county to the overall effect. That is, we can assess whether the exclusion of that county increases or decreases the overall change in NTL and, consequently, whether that country did comparatively better or worse than the average county affected by the hurricane (consult Methods for details).

Figure 2 portrays the direction and magnitude of the difference between the overall light change for a storm, and the light change when each county is omitted from the model. In the legend, we interpret the direction of these values as presented previously in table 1. In the cases of Hermine, Matthew, Harvey, and Dorian, which demonstrate overall negative changes in radiance due to the storm (portrayed on

Table 2. Average effect of individual hurricanes on nighttime light intensity in those areas eligible for combined storm-related FEMA aid, and individual-level only FEMA aid. Coefficients on the two variables of interest (the provision of combined, and individual-level only aid) are presented. These coefficients indicate the average percent change in nighttime light intensity in areas receiving the respective types of aid and are calculated separately for each hurricane. Their corresponding *p*-values are presented in the following columns. For these models, the entire available time series is considered. The number of months after the hurricane is presented in the 'Months Post' column.

Hurricane	Combined Aid	Individual Aid	*p*-Value, Combined	*p*-Value, Individ.	Months Post
Hermine	−2.926	−4.034	0.612	0.596	52
Matthew	−12.127	−14.747	0.000	0.000	51
Harvey	−1.846	−1.575	0.001	0.013	41
Irma	—	−11.868	—	0.000	40
Florence	0.901	3.616	0.501	0.025	28
Michael	3.428	7.018	0.232	0.018	27
Dorian	−9.829	—	0.001	—	16

Figure 1. Change in nighttime light radiance over time by storm, evaluated over the whole period up to the end of a given month with FEMA aid expenditure, by month. Panel (a) shows the overall percent change (or mean difference between the pre-period and the post-period between treatment and control counties, as defined by a given time cutoff) in NTL up to and including a given month in those counties eligible for combined aid over time. Panel (b) shows the same overall percent change in lights for those counties eligible for individual-level aid from FEMA for that storm. In both cases, FEMA's aid expenditure (expressed in log) determines the thickness of the line and is expressed in millions (USD) in the legend.
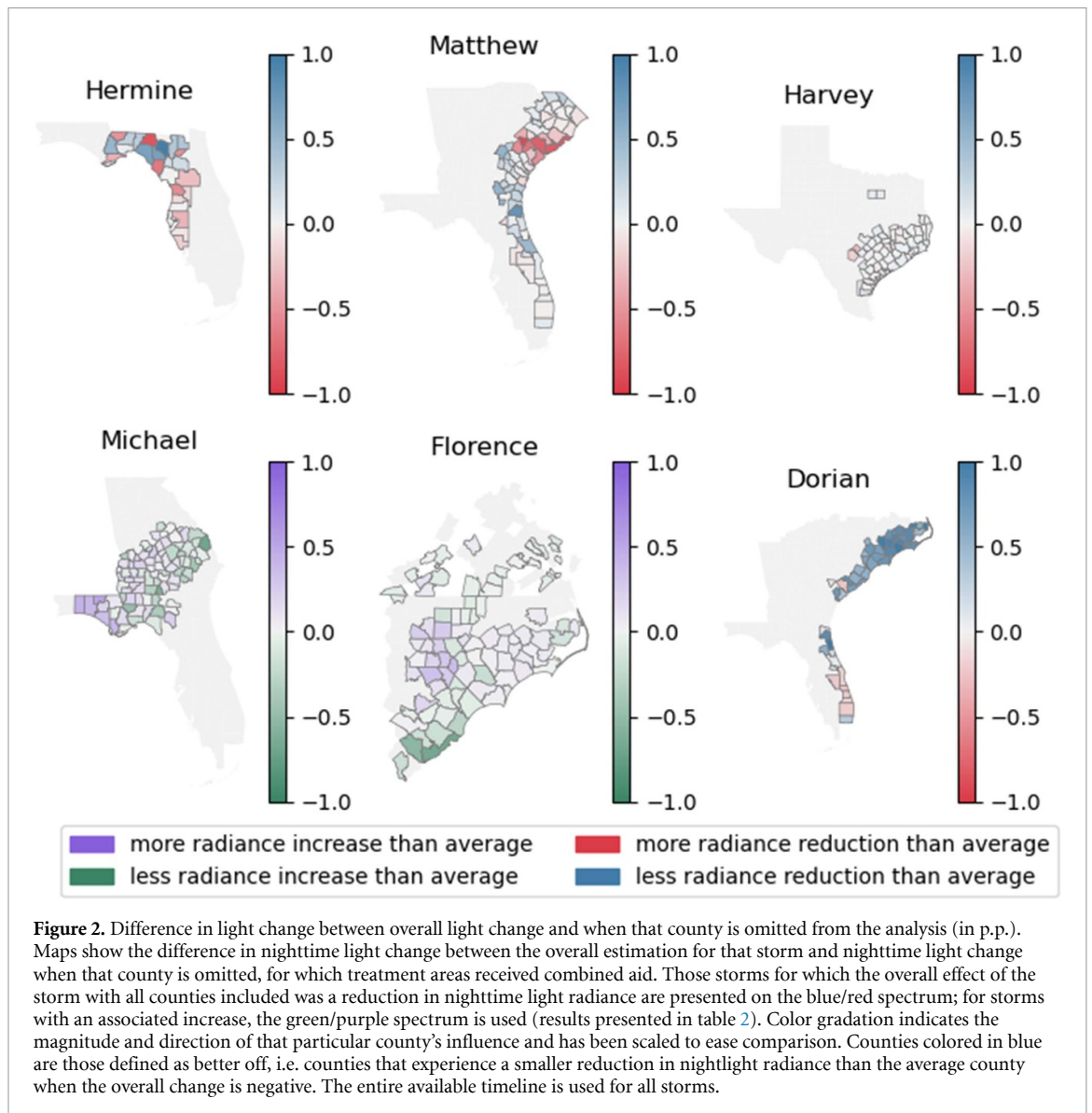
the red/blue spectrum), we see a diversity of county-level responses to the storm when we omit each county from the empirical model. There is a similar diversity in response to the storm on the county level for those storms demonstrating an increase in NTL after the storm (purple/green spectrum). In both cases, within the treatment group, counties perform diversely, even in storms where the overall effect of the storm is of a large magnitude. There do not appear to be geographic patterns in the dispersion of positive or negative county-level influence. Results from the models including counties eligible for just individual-level aid are included in supplementary figure 17.

3.3. Time and FEMA aid designation affect factors facilitating recovery

We next investigate those socioeconomic and demographic factors that most strongly determine the likelihood of a county having experienced a smaller reduction in NTL compared to the average (being 'better off'). Employing a tree-based machine learning approach, we back out the feature importance scores for the features used to predict each county's likelihood of being better off.

In figure 3, we provide the comparative importance of each feature in determining if a county was better off, and the direction of their effect for each of four time periods and each of the

Figure 2. Difference in light change between overall light change and when that county is omitted from the analysis (in p.p.). Maps show the difference in nighttime light change between the overall estimation for that storm and nighttime light change when that county is omitted, for which treatment areas received combined aid. Those storms for which the overall effect of the storm with all counties included was a reduction in nighttime light radiance are presented on the blue/red spectrum; for storms with an associated increase, the green/purple spectrum is used (results presented in table 2). Color gradation indicates the magnitude and direction of that particular county's influence and has been scaled to ease comparison. Counties colored in blue are those defined as better off, i.e. counties that experience a smaller reduction in nightlight radiance than the average county when the overall change is negative. The entire available timeline is used for all storms.

two treatment variables, combined public and individual aid and individual aid. As a robustness check, we also conduct the feature importance analyses using exclusively each of the tree-based algorithms tested and all time-cutoffs, regardless of performance. We find that while the specific point values differ, the general trends of how feature importances change as timelines increase, are preserved. These figures are included as supplementary figures 18–20.

In the case of combined aid shown in Panel (a) of figure 3, the total amount of FEMA aid is the most important feature across nearly all time horizons. After three months, the direction of its influence switches from positive to negative, where it remains, indicating that a larger total cost for a storm makes it more likely in the very short-term (up to three months) and less likely thereafter that a county is better off. It is intuitive there may be a negative correlation between aid and being better off, due to the fact that the provision of aid is likely linked to stronger

storm impact, though this may be ambiguous given that FEMA aid is provided with the explicit purpose to aid in the recovery of areas affected by disasters. In our data, we see that combined aid seems to fulfill this aim in the short term, as a larger amount of aid is associated with a higher likelihood of an area being better off. However, this effect reverses as the timeline continues, suggesting that aid may not be sufficient to motivate full recovery.

In the case of individual-level aid alone, the importance score of the cost of individual aid to FEMA is consistently negative across all time scales, indicating that a county with larger cost will be more likely to have a stronger reduction in NTL than the average for that storm. Additionally, employment, income, and age become increasingly important factors in the individual-level aid case, suggesting that they may support recovery and mitigate the effect of hurricanes. Results for those counties which experienced an increase in light after the storm are available in supplementary figure 21.
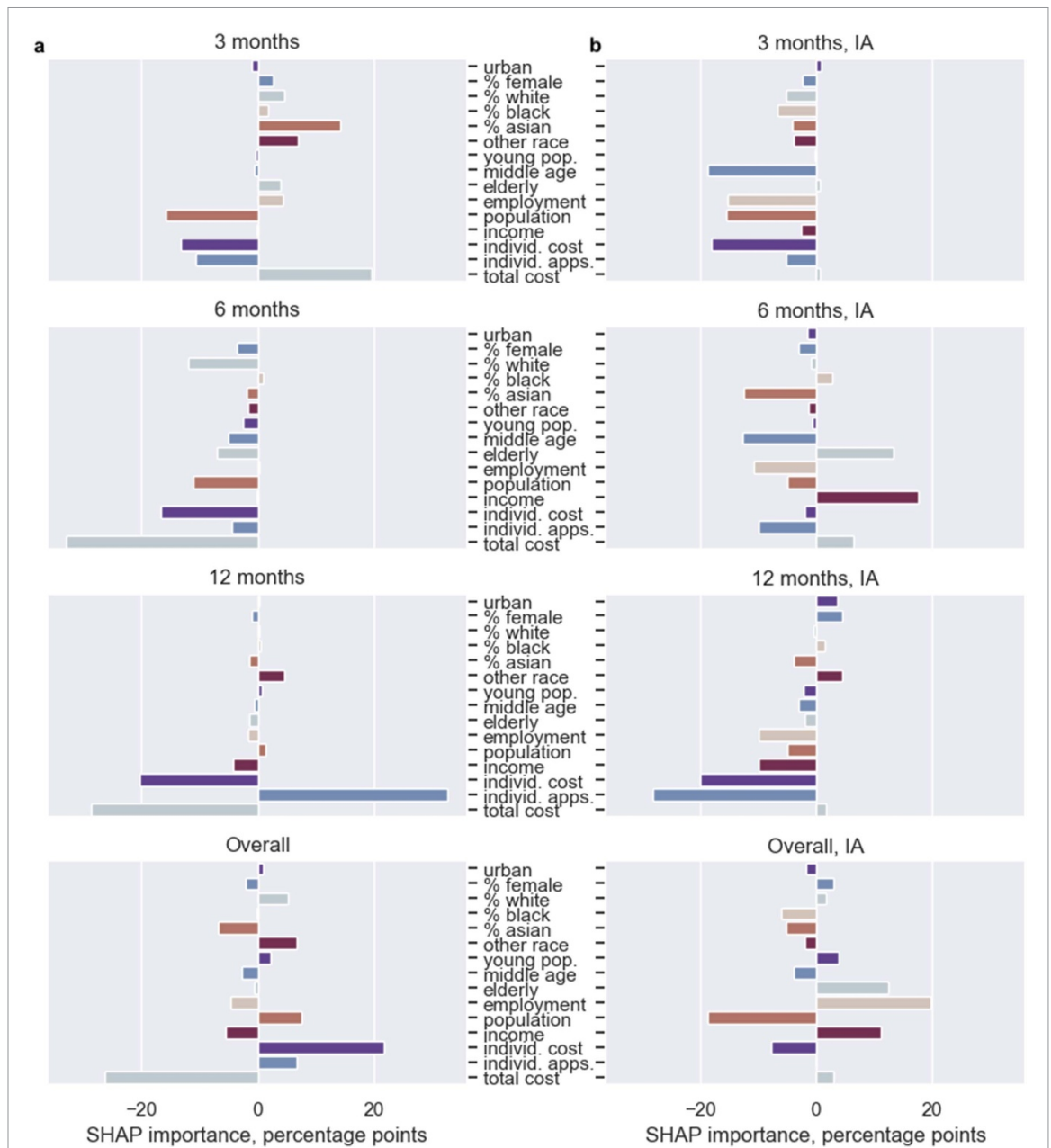
Figure 3. Comparative importance of different factors explaining why a county demonstrates a smaller reduction in lights than the aggregate reduction. SHAP importance measures the average impact each feature has on the model output (expressed as a percentage of all features' explanatory power). Larger bars indicate that the feature is more important to the model. Negative values indicate the feature reduces the likelihood that the county is better off than average; positive values indicate the feature increases the likelihood of a smaller reduction in lights than the average. Panel (a) shows the feature importances for the model including those counties receiving combined aid, Panel (b) shows the feature importances for the model including those receiving individual-level FEMA aid alone. Comparative importances are provided for four periods (3, 6, and 12 months after the storm as well as the overall timeline, which can range from 52 to 16 months, dependent on the storm. Compare to figure 1).

At the six month time window, and especially in the case of individual-level aid alone, we see a strong trend in most factors predicting negatively. This can be explained by the fact that the overall proportion of counties considered to be better off are fewest for this time horizon (supplementary figure 22).

Viewing all timelines and treatments in aggregate, the three FEMA aid related variables (total cost, individual applications, and individual cost) consistently affect the likelihood of a county being better off.

Reconstructing the analysis omitting variables relating to the quantity of FEMA aid, we find that higher income has a consistent positive influence on the likelihood that a county is better off, which is more pronounced for those counties having received individual level FEMA aid (full results are included in supplementary figure 23.) This suggests that income has a moderating effect on the reduction of light due to hurricanes, especially in those areas most significantly affected by the disaster.

4. Discussion and conclusions

Our results shed light on the dynamics and motivators of disaster recovery. Using NTL data, we find evidence that those areas of the United States affected by Category 4 and 5 hurricanes between the years 2014 and 2020 generally do not show a full return to previous radiance levels, especially three years or longer after the storm. This finding supports existing literature suggesting that disaster-hit areas do not demonstrate full economic recovery, though this research addresses significantly longer timescales (20 years post-disaster) [9]. Given the time granularity of our data, we are able to investigate recovery dynamics month by month to provide a more detailed timescale than previously studied. We find that many areas affected by hurricanes demonstrate large fluctuations in radiance in the short term (both positive and negative) but those storms with the longest time frames do not return to the levels of NTL radiance they demonstrated previous to the storm.

VIIRS NTL data have been shown to be well correlated to economic activity and population density [24–27, 47]. Our results suggest that areas affected by hurricanes may experience a lasting reduction in economic activity, population density, or both. These findings support previous evidence on the recovery-dampening effects of out-migration from hurricane-affected areas [8]. It is difficult to distinguish between these motivators without further data on migration or business activity, or more granular data on the extent of damage in the areas affected by these storms. Without these data, it is possible that part of the reduction in radiance we see is due to 'rebuilding better' where areas affected by the storm do experience a full recovery, but simply emit less light due to new, more energy-efficient infrastructure.

Data on the extent of damage due to the storm exogenous to both economics and population density (not derived from the costs of reconstruction or insurance claims) would enable a more precise identification of those counties affected by the storm. Eligibility for FEMA aid is a strong but imperfect proxy for the effect of the storm. It is possible that counties neighboring those eligible for FEMA aid were damaged by the storm, but at a level that did not warrant FEMA aid [48]. While this may muddy the difference between our treatment and control groups, this leakage would lead to an underestimation of the effect of the storm on the treatment counties, indicating that the true effect of the storm was larger than presented here.

Of those factors contributing to a below-average light reduction after a storm, we find that for all periods after three months, the quantity of FEMA aid received by the county is most influential. Given NTL radiance's strong correlation to economic activity, it may be that aid to public entities drives immediate recovery. Similarly using VIIRS NTL data, Chen and

Nordhaus [26] suggest that the types of economic activities best captured by NTL are those dependent on power for lighting at night, such as service, retail and transportation [4]. This could mean that these industries are fastest to recover with an influx of aid, and may motivate the rebound in radiance we see in the first few months after Hermine, Matthew, Michael and Dorian. The change in direction after three months suggests that FEMA aid may be integral to very short term recovery, as has been found in previous work [15, 16], but does not create sustainable recovery in the long term. This highlights the importance of analyzing longer time scales for a comprehensive overview of recovery dynamics.

When considering just those counties in which individual-level post-disaster aid was available, we find the factors most important in determining the likelihood of being worse-off than average are related to individual-level FEMA aid (total number of individual-level FEMA applications and the total cost of those applications). Similarly, in the case of those areas demonstrating an increase in NTL radiance after the storm, we find larger amounts of aid to be correlated with an even larger increase in light than the average (supplementary figure 21). This supports the hypothesis that while short term recovery is motivated by firms, longer term recovery is sustained by individuals.

When examining the full available timeline, economic and demographic factors such as employment and the proportion of elderly in the population usurp those related to individual-level aid, suggesting that socioeconomic status and age may play a role in the decision to rebuild or move from areas affected by a hurricane. Our finding that areas with larger elderly populations are more likely to demonstrate less NTL reduction than the average suggests that elderly populations may be more likely to return to hurricane-hit areas than younger residents. Though highly moderated by levels of severe housing damage, Fussell *et al* [49] also found this trend in studying the return to New Orleans after Hurricane Katrina, where two thirds of individuals over 40 returned after 14 months, compared to only half of those under 40 [49]. Similar to our results indicating that employment and income are positively related to the likelihood of a county recovering, they also find a reduction in the likelihood of migration with an increase in socioeconomic status. Using education as a proxy for socioeconomic status, they find that half of individuals with college degrees returned within four months of the storm, compared to 14 months for individuals without.

Some areas considered in this study were hit by several hurricanes during the timeframe of our analysis. As we do not have data on the number of hurricanes experienced by each area previous to the beginning of our dataset, it is difficult to determine the possible accumulated effect of

multiple hurricanes over time on the recovery or out-migration process without biasing our data on more recent storms. In the case of Hurricane Harvey which hit Texas, an area less frequently hit by hurricanes, we see a comparatively small, though negative, long-term change in NTL radiance. This suggests that the reduction in NTL radiance we see due to other storms in more frequently affected areas may indeed be motivated by accumulated disasters, perhaps by making individuals more likely to out-migrate or be reluctant to rebuild.

While we study a large geographic area, it is difficult to know how readily our results are generalizable to other regions affected by hurricanes, or other types of natural disasters. Especially given the importance of FEMA aid in determining county-level outcomes, it is difficult to generalize to regions with different disaster aid schemes (or none) or those areas with lower levels of development. Further research is required to understand whether, and to what extent, these results may apply to other regions.

Our results indicate the recovery of pre-storm levels of economic activity and population may be dependent on more long-term individual aid support. As extreme weather events become more frequent and intense, it is possible that this support must also be provided in new forms. Currently FEMA aid covers emergency disaster-related expenses and repair costs on the public and individual level. Our findings about the interaction of socioeconomic class and age in long-term recovery suggest that new forms of aid, such as those that encourage sustainable, disaster-informed rebuilding or that encourage individuals to take proactive measures in areas frequented by hurricanes, may be key to preserving future economic prosperity and manage hurricane-induced migration.

Data availability statement

The dataset was constructed from publicly available data [36–40]. The combined dataset, containing nighttime light radiance values, socio-economic and demographic information, as well as disaster-related data from FEMA is available upon request.

Code availability

The code used for the analysis and plots is available upon request.

Acknowledgments

Author contributions

Conflict of interest

The authors declare no competing interests.

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