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Nighttime Lighting Data as a Proxy for Hurricane Strength

Introduction

For an observer in space, the surface of the Earth appears simply as a series of landmasses interspersed among the sea. But on the night side of the planet, facing away from the Sun, a completely different story is told: brilliant artificial lights illuminate the surface, a clear indicator of human activity. Using this light as a data source has massive implications for visualizing and understanding human systems. Since 2012, NASA's Black Marble dataset has kept daily snapshots of this surface lighting data. Satellite images taken in regular intervals are combined to form a single set of nighttime light (NTL) data for a given day. The image data is then filtered and modified to account for environmental factors like atmospheric conditions, providing a rigorous, quantitative record of the artificial light emitted from human sources. By tracking changes in lighting data over time, many different social and environmental phenomena can be visualized in terms of human-generated light. With this method, data is standardized on a global scale, not reliant on compiling data from independent sources or having concern whether data is available or not (Stokes et al., 2019). Migration, population changes, energy access, and so much more can easily be viewed across the globe.

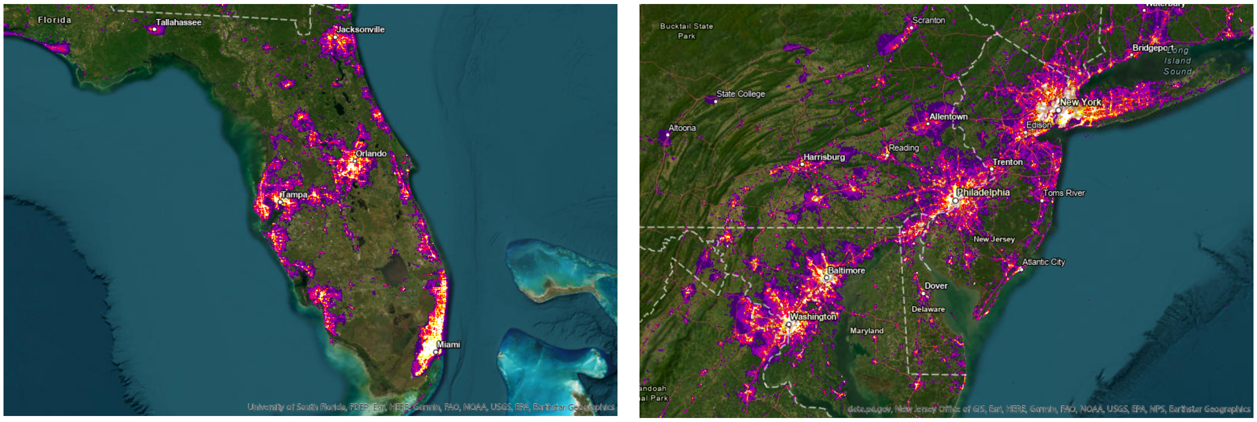


Figure 1. Visualizations of NTL data for *a)* Florida and *b)* the Northeast Corridor, displaying the significant presence of lights around highly-developed metropolitan areas.

The data from the Black Marble product suite has been used to investigate socioeconomic changes and urban developments, which can be viewed on large scales in urbanizing nations like India by comparing NTL data across time (Li et al., 2022; Satheendran et al., 2022). Some studies have used the dataset to assess the impact of light pollution on wildlife (Ditmer et al., 2021), the impact of the war in Ukraine on civilians living in warzones (Zheng et al., 2022), and optimization of waste collection in cities (Karimi et al., 2022). Other researchers compared lighting data before and during COVID-19 lockdowns to evaluate the impact of the pandemic on global economies and create an assessment of quarantine practices in various parts of the world (Dasgupta, 2022; Stokes & Roman, 2022; G. Xu et al., 2021). This wide variety of use cases shows the extensive power of NTL data, when tracked and analyzed over some time interval, to evaluate and improve human systems.

Perhaps the most striking and most beneficial application of the dataset in this way is with disaster recovery. Power outages–the data of which is hard to compile based on the limited capabilities of utility companies–are immediately recognizable via NTL data, providing global monitoring of the electricity grid and crucial knowledge for recovery crews in disaster-stricken areas (Core et al., 2022; Roman et al., 2019; Wang et al., 2018). This approach is also extremely helpful for the rebuilding process. Multiple researchers have conducted studies on the recovery of Puerto Rico after Hurricane Maria in 2017, showing the potential of NTL data in monitoring the rebound of the power grid and accelerating recovery efforts in places which lack enough comprehensive data collection infrastructure to do so alone (Elkins, 2019; Machlis et al., 2022; Roman et al., 2019). There are also studies investigating short-term population changes as people are displaced by disasters (Enenkel et al., 2020), and others investigating community resilience after disasters strike (J. Xu & Qiang, 2021).

Despite the existence of prior research analyzing the effects of individual storms using NTL data (Elkins, 2019; Roman et al., 2019; Wang et al., 2018; J. Xu & Qiang, 2021), there have not yet been studies comparing the data between different storms. As a first step in this untapped area of research, we investigate whether or not there is a relationship between the NTL difference during a storm's impact and the strength of said storm. We look at how different storms have caused different NTL outcomes, and try to expand the research capabilities of NTL data beyond just locating hurricane damage to actually describing the hurricane itself. To accomplish this, we compare lighting changes during the impacts of a vast selection of hurricanes, looking for patterns among highly-affected areas, to determine whether the hurricane's reported strength matches what is observed in the damage. Ultimately, we find that NTL data, although not quite perfect, is able to distinguish between major and minor hurricanes, and is somewhat indicative of the hurricane's strength. This highlights the potential of NTL data to be used even more extensively in the future to make new discoveries about hurricane response, prompting further research into NTL's analytical capabilities.

Materials & Methods

Research Goals

The comparison of NTL data across time offers an advantageous bird's-eye view into areas plagued by natural disasters when other data collection methods fail. While previous research has shown that hurricane damage can be observed through analysis of NTL data, in this study we go a step further by comparing and analyzing the NTL data of *many* hurricanes. We focus on one main objective: since it is known that NTL data has the capability to identify storm damage, and that stronger hurricanes will obviously inflict more damage, we seek confirmation that there are observable differences between the NTL changes associated with different hurricane strengths. This finding would further confirm that analysis of NTL is a valid research method for investigating natural disasters; beyond just marking the mere *presence* of hurricane damage, it would mean NTL data is powerful enough to reveal *characteristics* of hurricanes as well.

Black Marble Data

To obtain the lighting data for the disasters we wish to observe, we extracted data from the NASA Black Marble VNP46A1 product, a publicly available NTL dataset which provides daily lighting measurements for the entire globe at 15 arcsecond resolution. We obtained and organized the data for the desired dates and locations via Bash scripting and loaded it into a geospatial analysis software, ArcGIS Pro. The data is organized into HDF5 files each representing a tile of Earth's surface on a specific date, covering an area of 10° longitude x 10° latitude. Tiles are identified by their horizontal and vertical position on the Earth projected onto a flat 2D surface. The dataset's *DNB At Sensor*

Radiance value provides the radiance of the day-night band in $nW/cm^2/sr$, averaged over 15 arcseconds, or about half a kilometer (Roman, 2022). This represents a sample of the amount of light emitted from a given area of the surface throughout the day.

Hurricane Sample

For this study, we will look at all Atlantic hurricanes which have made landfall in the continental United States since 2012, when NASA began daily NTL data collection. Since hurricanes grow and diminish in strength over time, it is important to note that we will be considering the strength of the hurricane at the time it made landfall, and not the maximum strength it reached offshore. We will only consider actual hurricanes, not tropical storms, meaning the storm must have had sustained wind speeds of at least 74 mph (64 knot) at the time of impact. This leaves us with 21 hurricanes that have made landfall in the U.S. since 2012. The sample of hurricanes is summarized in **Figure 2**.

Name	Category	Landfall Date	Location	Wind
Isaac	1	Aug 28, 2012	LA	70
Sandy	1	Oct 29, 2012	NY/NJ	65
Arthur	2	Jul 3, 2014	NC	85
Hermine	1	Sep 1, 2016	FL	70
Matthew	2	Oct 8, 2016	FL	85
Harvey	4	Aug 25, 2017	TX	115
Irma	4	Sep 9, 2017	FL	115
Nate	1	Oct 7, 2017	LA/MS	65
Florence	1	Sep 14, 2018	NC	80
Michael	5	Oct 10, 2018	FL	140
Barry	1	Jul 13, 2019	LA	65
Dorian	2	Sep 6, 2019	NC	85
Hanna	1	Jul 25, 2020	TX	80
Isaias	1	Aug 4, 2020	NC/SC	80
Laura	4	Aug 27, 2020	LA/TX	130
Sally	2	Sep 16, 2020	FL/AL	95
Delta	2	Oct 7, 2020	LA	85
Zeta	3	Oct 28, 2020	LA	100
Ida	4	Aug 29, 2021	LA	130
Nicholas	1	Sep 14, 2021	TX	65
Ian	4	Sep 28, 2022	FL	130

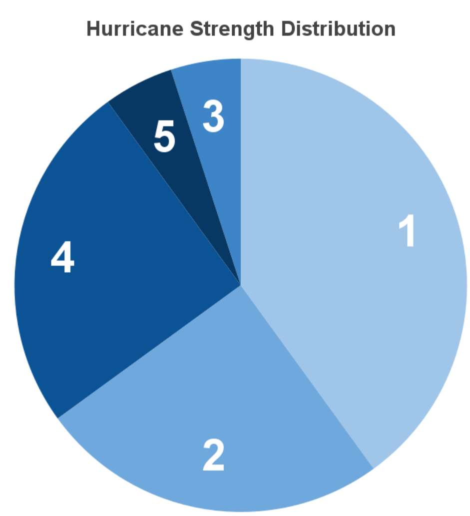


Figure 2. Overview of the hurricanes used in the study, describing their strengths, landfall dates and locations, and wind speeds in knots. Data obtained from NOAA.

Methodology

For each storm, we first observe NTL data before and after the hurricane's impact, noting any changes between the two. There are two measurements for each hurricane: one data point a few days prior to its landfall, and another a few days after it. This combination gives a reasonable indication of the hurricane's effect on the area in which it made landfall. ArcGIS Pro is used to render the visualizations of the area and compare data between the two instances. The radiance is color-coded to represent the amount of light emitted from a given area; areas with radiance less than 25 $nW/cm^2/sr$ are omitted. After that, NTL data before the storm is subtracted from NTL data after the storm to get a net change in NTL. This difference is visualized on a separate map with its own color-coded values, allowing us to see which areas were affected the most.

Next, we overlay the paths of the hurricanes, available from a public dataset provided by the National Hurricane Center. For this study, we will focus on areas within 40 km of the path, defining these as the main locations in the path of the storm. We look at the trajectories in combination with the difference in NTL over the hurricane's impact, and identify the areas that are the most hard-hit. Areas which have suffered major power outages are easily identifiable as they have lost a substantial amount of light. On the other hand, a mix of increases and decreases indicates there was no overall change. We take into account the proximity of the highly-affected clusters to the eye's path, and by observation, we are able to get a sense of their distances from the center of the storm, and thus the fraction of its full power they endured.

To more rigorously compare the differences in NTL data across the different hurricanes, we take a more statistical approach beyond just qualitative analysis, and calculate the percent change in total NTL data within the hurricane's path between the two observations. This single metric gives us a reasonable estimate of the damage inflicted by the hurricane and allows us to compare the entire dataset all at once. To get a more accurate picture of the damage inflicted, we only consider the data within the aforementioned region: all areas within 40 km of the path of the eye. For each snapshot, we sum the NTL data in ArcGIS Pro, adding up the radiance of each individual pixel within the region, and find the percent change of the total. This measurement of the change in total artificial lighting emissions gives us a good indication of the amount of damage done by the storm. We then plot the percent change against the hurricane's wind speed–which defines its strength–and determine whether a relationship exists.

$$NTL\ Percent\ Change\ = \frac{\sum_{pixels} NTL\ after - \sum_{pixels} NTL\ before}{\sum_{pixels} NTL\ before}$$

Limitations

There are various limitations with our approach of NTL analysis. For instance, there are issues interpreting how much light is actually coming from the surface when there is dense cloud coverage, which causes both dimming of the surface lighting and a significant amount of reflection from the clouds. These issues are unfortunately most prevalent when observing NTL data on a daily basis, as is required to observe these hurricanes over short time scales (Li et al., 2022). To account for this, we try to choose observation dates without major atmospheric alterations. Since the presence of the hurricane vortex itself causes these disturbances to occur, we try to make observations at least 5 days before and 5 days after the hurricane made landfall–this means that short-term damage and power outages which are resolved quickly, after only a few days, will unfortunately not be detected in this study.

The NTL difference between the two snapshots is useful as a control: we can ensure that the two snapshots are not wildly different by looking at the changes as a whole. Any significant overall change (i.e., in areas not impacted by the storm) would mean there are other factors–likely atmospheric–in play, rendering the data meaningless in the context of surface lighting changes. Therefore, for a snapshot to be used for this study, any area *not* impacted by the hurricane must have had minimal overall changes in lighting conditions, so that we can ensure the NTL change in areas which *were* impacted can actually be attributed to the hurricane. This means we must sometimes collect data 6, 7, or more days before or after, which may cause anomalies when comparing data between different storms. Even still, the atmosphere always plays a role in altering the lighting conditions, which is a limitation of NTL data itself.

Results

Validation of NTL as Indicative of Hurricane Damage

NTL data for the various storms is compiled and mapped into visualizations depicting the radiance emitted from the surface, with data before and after the storm, and the net change. With the overlay of the hurricane's path, we can immediately notice the stark decrease in lighting conditions in areas in close proximity to the eye, as evident in **Figure 3**. The lighting differences in areas most heavily impacted by the storm reveal significant power outages. This aligns our findings with those of previous researchers (Elkins, 2019; Roman et al., 2019; Wang et al., 2018), showing that NTL data is a useful tool at least in locating hurricane damage. With this established, we proceed to more closely analyze the differences between hurricane impacts.

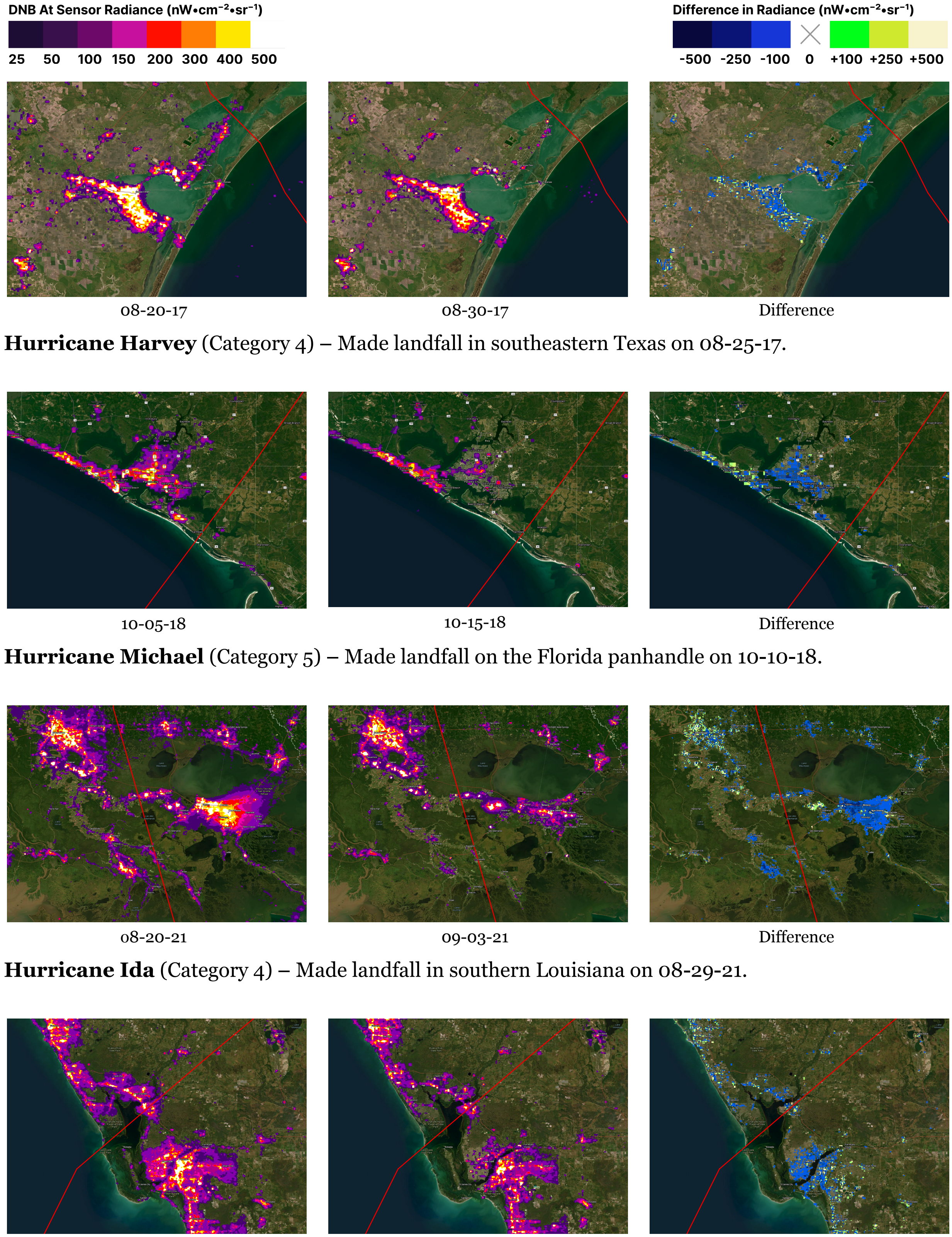
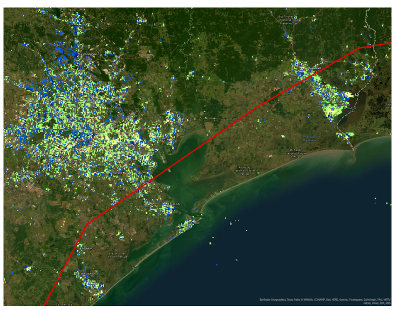


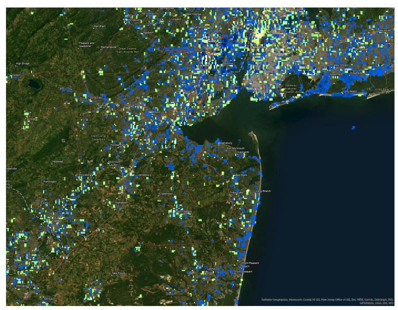
Figure 3. An overview of NTL changes in different areas during the impacts of four major hurricanes. Note the heavy decrease in lighting conditions in areas closest to the path of the eye (traced in red).

Qualitative Analysis of NTL Changes Across Hurricanes

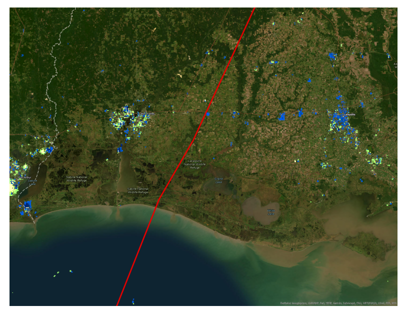
First we will consider qualitative analysis of the hurricane categories on the Saffir-Simpson scale by observing NTL changes in a variety of areas impacted by hurricanes. **Figure 4** shows the impacts of a selection of storms from each strength category in terms of NTL difference. The data shows that the stronger hurricanes, categories 4 and 5, are associated with the sharpest decreases in NTL. For the weaker hurricanes, categories 1 and 2, there appears to be no overall change, with pixels having a mix of increases and decreases in general.



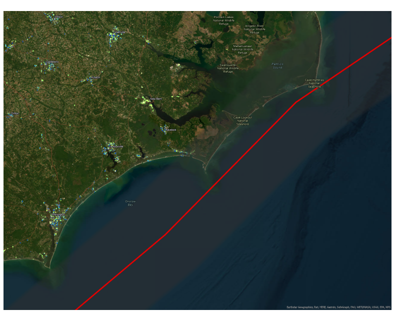
Category 1 Nicholas in Houston, TX



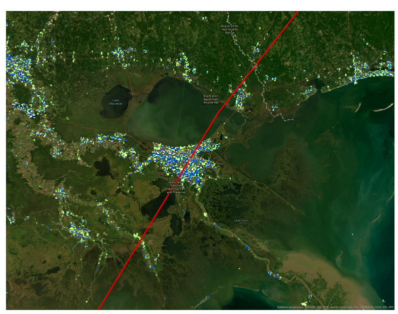
Category 1 Sandy in NJ & NY



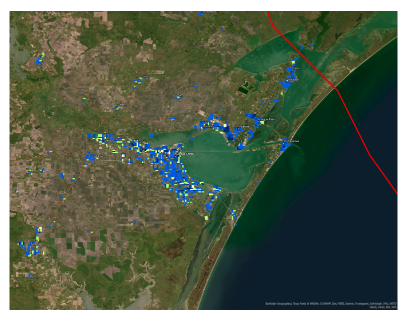
Category 2 Delta in southern LA



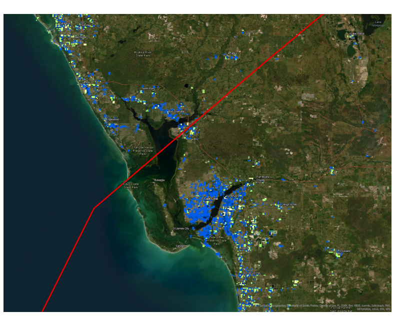
Category 2 Dorian on the NC coast



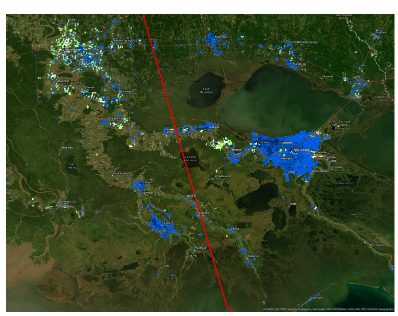
Category 3 Zeta in New Orleans, LA



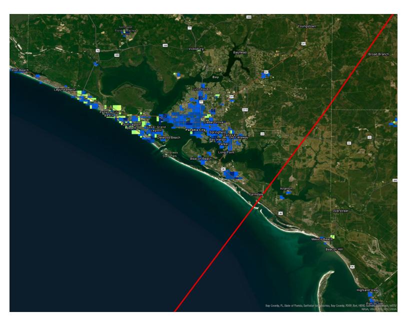
Category 4 Harvey in Corpus Christi, TX



Category 4 Ian in southwestern FL



Category 4 Ida in southern LA



Category 5 Michael in Panama City, FL

Figure 4. NTL differences during the impacts of a selection of hurricanes of various strengths. Note particularly the deep blue clusters, indicating sharp decreases in radiance.

Statistical Analysis of NTL Changes Across Hurricanes

In order to confirm our observations of NTL differences as correlated with hurricane strength, we will also take a more rigorous and numerical approach. For each hurricane, we calculate the percent change in total NTL between the two snapshots by summing all of the data within the hurricane's path as described, and calculating the percent change between the totals. The results of this are summarized in **Figure 5**.

Name	Category	Wind	Total Before	Total After	Net Change	%Change
Isaac	1	70				
Sandy	1	65				
Arthur	2	85				
Hermine	1	70	6186251	8747259	2561008	41.40%
Matthew	2	85	1740204	7881013	6140809	X
Harvey	4	115	8378034	5929129	-2448905	-29.23%
Irma	4	115	16290214	7765421	-8524793	-52.33%
Nate	1	65	24472547	21417741	-3054806	-12.48%
Florence	1	80	8189973	9845389	1655416	20.21%
Michael	5	140	8958316	9807357	849041	9.48%
Barry	1	65	4688972	13687274	8998302	X
Dorian	2	85	2443088	6517145	4074057	X
Hanna	1	80	1756045	1366234	-389811	-22.20%
Isaias	1	80	8803885	26789611	17985726	X
Laura	4	130	4646162	28147837	23501675	X
Sally	2	95	15069055	13610812	-1458243	-9.68%
Delta	2	85	8737713	4377265	-4360448	-49.90%
Zeta	3	100	11878122	43316396	31438274	X
Ida	4	130	26665006	11664892	-15000114	-56.25%
Nicholas	1	65	12036878	21747151	9710273	80.67%
Ian	4	130	4944519	5112037	167518	3.39%

Figure 5. Data describing the total NTL changes in each hurricane's path (specifically, the total radiance in $nW/cm^2/sr$) between snapshots before and after the hurricane's impact.

In this part of the study, we have had to reduce the sample size, firstly because the hurricane path data from NOAA only exists for storms that occurred in 2015 or later. Additionally, to ensure some accuracy of the data, we have eliminated outliers with percent changes beyond 100%, marked with an X. In these cases, the path likely goes over dense cloud coverage which skews the totals quite drastically. For instance, in the case of Hurricane Laura, the hurricane vortex itself is still visible in the second snapshot; even though it is significantly far away from the impact site, the path still runs through it, so there appears to be a massive increase in radiance. Also, almost all of the dates close to the impact of Hurricane Matthew were plagued with cloud coverage and high reflectivity. To account for these and other similar anomalies, we restrict the study from here to only include hurricanes with percent NTL changes less than 100% in magnitude. This way, it is much more feasible that the percent change observed is actually indicative of damage done by the hurricane.

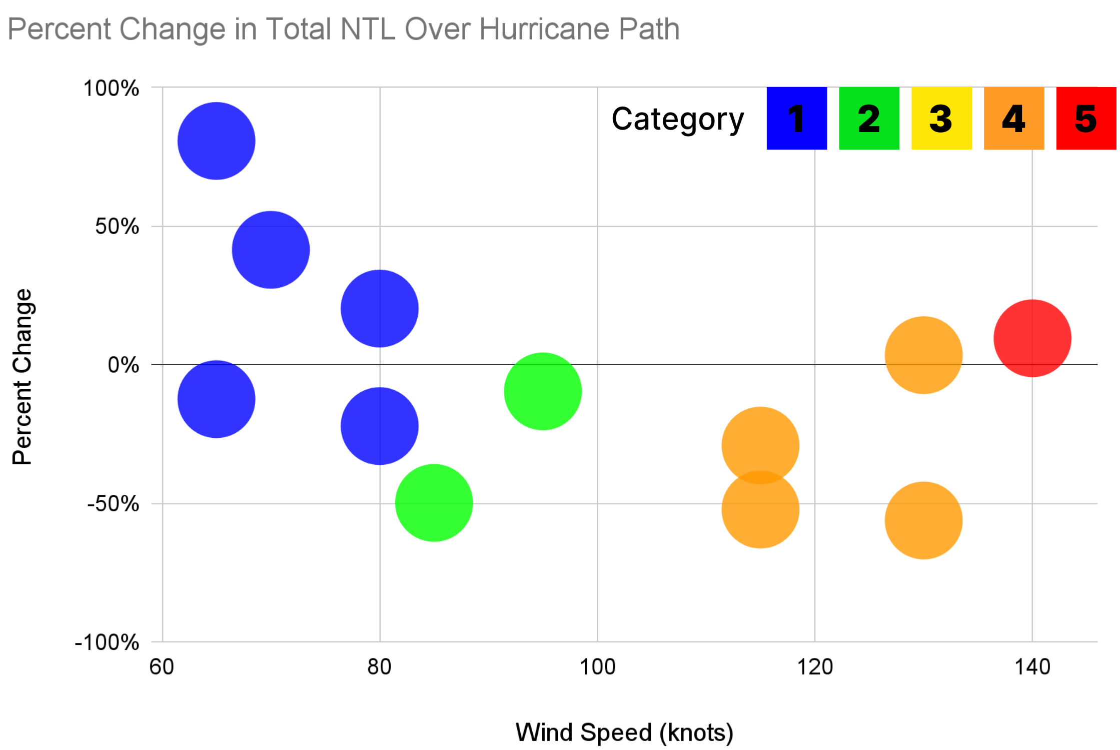


Figure 6. Scatterplot depicting the percent change in NTL over areas within 40 km of the hurricane's path, plotted against the hurricane's maximum recorded wind speed after making landfall. The storms' categories (determined by the wind speed) are encoded through colors indicated by the legend. Note that outliers were removed from the sample as described above, resulting in no Category 3 storms remaining.

By plotting the percent change in NTL data against the hurricane strength, as in **Figure 6**, we find that the strongest hurricanes in the sample caused the greatest reduction in NTL across the areas they impacted, and thus the greatest quantity of damage. Although the data does not appear very tightly correlated, and there are notable choices we have made to select the best representative data among a complex dataset involving many possible anomalies, we can nevertheless clearly see that in general, the impacts of major hurricanes (categories 4 and 5) are associated with decreases in NTL, while the impacts of less severe hurricanes show a mix of increases and decreases in NTL. Through the exclusion of a notable amount of our sample hurricanes in this specific analysis, although we have theoretically improved the accuracy of the result (i.e., that the NTL data we observed is more representative of artificial light from the surface), we have also limited the amount of data from which we can draw conclusions. While a more sophisticated analysis would likely result in a stronger relationship, we can still see that some relationship exists, as there is generally a difference between the NTL changes associated with major and minor hurricanes. Therefore, the data confirms that NTL is at least partially capable of measuring hurricane strength, and introduces the possibility that more rigorous statistical analysis in future studies would lead to more definite results.

Discussion

Key Findings

Our analysis confirms that NTL data can be used as a proxy for hurricane strength by analyzing the change in lighting emissions over the impact period of the storm. We find that the stronger a given hurricane, the more damage, in terms of NTL decrease, it will inflict on the area within its path. Although it seems like a trivial result, the fact that this behavior can be observed solely through analysis of NTL data is the part that is of interest to us. We are able to observe that changes in the lighting of Earth's surface can be related to the wind speeds of hurricanes, a seemingly unrelated phenomenon altogether. Therefore, the main takeaway of this pilot research is the methodology that was used to confirm the result. Although these are only the beginning stages, we have found that analysis of NTL data across the time period of the hurricane's impact can at least partially reveal actual characteristics about the storms, beyond merely the locations of highly-affected areas.

Future Directions

Our findings in this study prompt future research to discover more analytical capabilities of nighttime lighting data. There must be more rigorous, quantitative NTL data analysis conducted to further confirm that the characteristics of hurricanes can be viewed in terms of NTL differences observed within their impact locations. In the future, perhaps different types of statistical analysis could be performed to generate a more accurate measurement of the relationship between hurricane strength and NTL difference. Instead of measuring the total amount of NTL over the hurricane's entire path and finding the percent change, as was done in this study, the measurement area could be restricted to a specific zone around the hurricane's landfall location. This could prevent the collection anomalies we observed in NTL in areas further inland when cloud coverage could not be removed. Instead of trying to find snapshots with minimal atmospheric alterations over the hurricane's path, we could instead settle for snapshots with minimal alterations just over the area in which the hurricane made landfall.

Restricting the area to the landfall location only would likely prove useful in the comparative analysis between different storms, as it would ensure that the most affected areas are the primary locations represented within the data, giving us a standard with which to compare the hurricanes. However, there are also drawbacks to this, most notably that it would not represent the full extent of the hurricane's path. The NTL research sphere would also benefit from studies involving computer vision and clustering algorithms to more rigorously analyze NTL images which we were unable to accomplish through only qualitative analysis, further solidifying relationships between hurricane characteristics and NTL data.

This study also raises questions about NTL data and the Black Marble dataset, exhibiting some of its limitations. As noted in previous research, street lights in metropolitan areas account for a large portion of lighting emissions, and are often not fully representative of power outages in homes and other buildings (Roman et al., 2019). Also, although the dataset claims to have corrected for atmospheric conditions like cloud coverage, the effects of atmospheric anomalies are clearly visible in the research we have done. Other researchers have found that these anomalies only manifest on short time scales (Li et al., 2022), but this is necessary for a study about hurricane impacts, which occur over only a few days. This drawback requires working around the anomalies by only selecting data which does not drastically exhibit these effects. This is a major problem for short-term NTL studies, as future improvements made by the Black Marble team might be able to greatly increase the usefulness of NTL data for research purposes. Therefore, although we see a pattern, specific relationships cannot yet be assigned between NTL decreases and hurricane strength.

Regardless, this research opens up many new possibilities for use cases of NTL in the future. Used as a proxy for hurricane strength, perhaps NTL could soon play an even more important role in disaster relief. On the other hand, maybe by developing a rigorous model of this relationship and then reverse-engineering the phenomenon, the already-measured strength of a hurricane on a collision course with a coastal community could give us greater insight into the NTL changes that *will* occur when it inevitably strikes. Thus, NTL may be able to help us in predicting the extent of the damage that an approaching hurricane will cause. The combination of these two sources of information–meteorological data and nighttime lighting data–could be the catalyst for stronger predictive models of hurricanes in the future, which could potentially save lives. By integrating NTL into professional storm-tracking, meteorologists might be better able to predict and understand the impacts of hurricanes and tropical storms on civilization, and recovery crews might be better able to deliver help to those who are most affected by them.

Supplementary data to this paper is available online, with NTL included for all hurricanes used in the study: https://github.com/joerup/hurricane-ntl.

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This paper represents my own work in accordance with University regulations.

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