Rapid assessment of cyclone damage using NPP-VIIRS DNB and ancillary data

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Abstract

Rapid damage assessment of natural disasters is essential for the fast recovery and strategic post-disaster reconstructions. In the present study, National Polar-Orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) day/night band (DNB)-extracted night-time lights (NTL) data were explored for damage assessment caused by extremely severe cyclonic storm ‘AMPHAN’ that struck one of the most populous regions in India. The disaster impact was measured on two parameters: population and crop land area, where NTL density and population density were found to be strongly correlated ($r^2 > 0.8$). From power outage intensity, three ‘crisis zones’ indicating the severity of cyclone damage were identified. Finally, the assessment found that the total affected population and crop land area were nearly 70% and 66%, respectively, of the study area. Therefore, NPP-VIIRS DNB image-based rapid damage assessment is potentially a useful tool for generating first hand information about the physical damages caused by extreme events.

Keywords Night-time lights · NPP-VIIRS DNB · Cyclone ‘AMPHAN’ · Rapid damage assessment

1 Introduction

The night-time lights (NTL) measured from space have great potential for mapping and monitoring the dynamics of human activities on earth and understanding the related environmental impacts (Doll et al. 2006; Aubrecht et al. 2008; Chen and Nordhaus 2011; Elvidge et al. 2012; Addison and Stewart 2015; Zhao et al. 2018b, 2019). Electricity usage, an indicator to human health, well-being and economic productivity (Dora et al. 2015), have also been studied using the NTL data where a strong correlation between the two was established (Mann et al. 2016; Dugoua et al. 2018). Dimensions of disaster including

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damage and recovery have been studied extensively over last few decades (Kohiyama et al. 2004; Cao et al. 2013; Fan et al. 2018; Román et al. 2019) using NTL. Several studies have used nightlights data as a proxy indicator for collapse of local economic activities, infrastructural damage and loss of human settlements in post-disaster scenarios (Doll et al. 2006; Bennett and Smith 2017; Ishizawa et al. 2019). There is evidence that first-hand observations of NTL are useful in assessing power outages caused by natural disasters and that this information can help the Disaster Response Community and Emergency Management Professionals to coordinate life-sustaining disaster mitigation better (Kohiyama et al. 2004; Bertinelli and Strobl 2013; Zhao et al. 2018a). Availability of open-access NTL data from Defense Meteorological Satellite Program's Operational Line-scan System (DMSP-OLS) and NASA's Suomi NPP-VIIRS in Earth Observation domain has made them suitable for rapid disaster assessment. Daily satellite passes also ensure repetitive measurements of speed of recovery from disaster of remote and isolated areas that may be difficult to reach. NTL data have given the geospatial information community an opportunity to add a new perspective in disaster risk applications and disaster damage studies.

Natural disasters, such as cyclones, can seriously damage human settlements and infrastructures, resulting in reduction of human activities, all of which may lead to fluctuations in nightlight output. Thus, the affected area can readily be mapped by NTL and can estimate the size of the affected population. Although NTL images have been produced from DMSP-OLS since the early 1970s and they have been widely exploited for disaster assessment specifically in last three decades (Elvidge 1998, 2003), its image quality is limited by saturation in bright urban areas, a low spatial resolution, and lack of onboard calibration (Bennett and Smith 2017; Wang et al. 2018; Zhao et al. 2019). The next-generation NPP-VIIRS day/night band (DNB) data provide improved NTL products compared to DMSP-OLS due to the inclusion of a full in-flight calibration, a finer radiometric quantization, a higher spatial resolution and a wider dynamic range (Miller et al. 2012; Elvidge 2013; Román et al. 2018). This has facilitated the geospatial information community to use it widely across diverse spatial and temporal scales (Sharma et al. 2016; Guo et al. 2015; Yu et al. 2015; Zhao et al. 2019).

The changes in NTL due to strong cyclonic storms provide valuable information about the disaster impact, which can be extracted from pre- and post-disaster NTL images. Currently, the daily NPP-VIIRS DNB data are widely applied by the geospatial communities for disaster monitoring to estimate the abrupt changes of power delivery caused by disasters and their pace of restoration. Cao et al. (2013) found close agreement between power outage range extracted from NPP-VIIRS DNB data and power company survey data, during two extreme storm scenarios in the USA. Molthan et al. (2013) used daily NPP-VIIRS NTL data to identify potential areas of power outage by producing false-colour-composite images for pre- and post-hurricane phase. Wang et al. (2018) used Black Marble VNP46 NTL product for calculating pixel-based percent of normal NTL for detecting the spatial extend of power outage caused by Hurricane Sandy on the north-eastern coast of the USA. Román et al. (2019) derived Normalized Difference Urban Index at higher resolution from NASA's Black Marble product suite to detect power outages and recovery time after Hurricane Maria. Zheng et al. (2019) used NPP-VIIRS DNB daily data for rapidly assessing the damage by the super-typhoon Maria that caused landfall in the urban agglomerations along the western Taiwan Straits in China. Overall the pixel-based comparison of pre- and post-event images and region-based time series analysis are the most commonly used methods for detecting changes in NTL remote-sensing images (Zhao et al. 2018a; Zheng et al. 2019).

The distinct geo-climatic location and the great physiographic diversity of India has made it one of the most disaster-prone countries of the world, and it annually loses nearly 2 percent of the GDP due to disasters (NCRMP 2020). After floods and droughts, cyclones are the most frequent disaster in India. On average, five to six cyclones hit India every year of which two or three could be severe. With a coastline of about 7516 km, the country is exposed to nearly 10 percent of the world's tropical cyclones (MHA 2010). The ratio of occurrence of cyclones between Bay of Bengal and Arabian Sea is approximately 4:1, and an annual number of storms to severe storms is highest in the Orissa–West Bengal coast. Besides high mortality, economic loss from cyclones is also relatively high in the region. Very recently, this region has encountered one of the worst cyclones in decades, causing huge damage and destruction along its path. The north–north-eastwards-moving extremely severe cyclonic storm ‘AMPHAN’ had the landfall near Sundarbans, India, by late noon on 20 May, 2020. As per the initial West Bengal state official statement, the cyclone has claimed at least 72 lives and damage of approx. \$13 billion to infrastructure and crops.

This study demonstrates the ability of the NASA's Suomi NPP-VIIRS DNB data to detect power outages following the landfall of cyclonic storm ‘AMPHAN’. Mapping the power outage in the aftermath of a disaster can work as a first hand tool to estimate the impact and loss. The present study measures the changes in power accessibility for pre- and post-disaster phases for selected districts of West Bengal state, India. This works in a direction towards generating first hand information on cyclone losses with reference to the affected population and affected crop land area. Rapid assessment of cyclone damage can help the disaster managers to plan measures for the fast recovery and mitigation.

2 Material and methods

2.1 Study area

Being a warm sea, Bay of Bengal is a potentially energetic region for the development of cyclonic storms that accounts for approx. 7 percent of the global annual total (Gray 1968). The north–northwest coast of Bay of Bengal is one of the regions of India most affected by tropical cyclones of severe nature. In terms of frequency of occurrence, there are two sharp peaks in a calendar year: one in October–November and another in April–May (Gray 1968). During 1891–2002, approx. 70 percent of the major cyclones in India had occurred in the three states of the region: West Bengal, Odisha and Andhra Pradesh (NCRMP 2020). The West Bengal state itself encountered 69 major tropical cyclones during the period; with most affected districts identified were East and West Medinipur, and South and North 24 Parganas.

The north–north-eastwards-moving extremely severe cyclonic storm ‘AMPHAN’, with a wind speed of $155\text{--}165\text{ km h}^{-1}$ gusting to 185 km h^{-1} , crossed West Bengal–Bangladesh coasts between Digha (West Bengal, India) and Hatiya (Bangladesh) near Sundarbans between 1530 and 1730 h IST (India Standard Time) of 20 May, 2020 (Fig. 1). Kolkata (Dum Dum) reported 130 km h^{-1} at 1855 h IST. Few places in the region mainly over Gangetic West Bengal (East and West Medinipur, South and North 24 Parganas, Howrah, Hugli, Kolkata and adjoining districts) received heavy to very heavy rainfall. According to Indian Meteorological Department, the supercyclonic storm ‘AMPHAN’ had the landfall at 1530 h IST and after crossing West Bengal, India, it weakened into a deep depression at 1130 h IST of 21 May, 2020, over Bangladesh near latitude 25.0°N and longitude

Fig. 1 The path of extremely severe cyclonic storm ‘AMPHAN’ (UTC–Coordinated Universal Time; IST–India Standard Time)

89.6°E about 300 km east–northeast of Kolkata (for further information related to the genesis, morphology and movement of the cyclonic storm, refer to ‘Super Cyclonic Storm ‘AMPHAN’ over the southeast Bay of Bengal (16th–21st May 2020): Summary’ at https://internal.imd.gov.in/press_release/20200614_pr_840.pdf).

The study area includes all the districts, except Puruliya, of southern part of West Bengal, i.e. the districts on the south of River Ganga, and they are specifically lying within the buffer of 200 km from the cyclone path. The term ‘district’ represents an administrative unit of an Indian state.

2.2 Data sources

The NASA NTL data are derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument onboard the Suomi National Polar Partnership (NPP) satellite launched in October 2011. The high-quality NTL data, derived from the processing of 6 min of NPP-VIIRS DNB (day/night band) data, have a swath width of 3000 km and a spatial resolution of 750 m at nadir. The NTL data are produced following the methodology provided by Elvidge et al. (2017). DNB is a panchromatic channel covering the wavelengths from 500 to 900 nm and is sensitive to visible and near-infrared during daylight hours as well as the low-level radiation observed at night. The present study has considered VIIRS/NPP DNB 6-Min L1 Swath SDR 750 m data (for further information visit: https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/NPP_VDNES_L1/). The daily estimates of NTL for three dates, 17 May 2020 for pre-cyclone phase and 22 May 2020 and 23 May 2020 for post-cyclone phase, were downloaded.

At the same time, for the purpose of the cyclone damage assessment, population and land use/land cover data were also incorporated in the study. In addition, the path of extremely severe cyclonic storm ‘AMPHAN’ was derived from the India Meteorological Department Cyclone Warning Division. Population data were obtained from WorldPop data sets (Fig. 2a) and high-resolution land-cover data of the study area were obtained from ISRO-Bhuvan portal (Fig. 2b). The details of the data used are listed in Table 1.

2.3 Data preparation

The daily estimates of NPP-VIIRS DNB data contain inevitable features and noises, such as atmospheric cloud cover, flare points, lightning and moonlight contamination. Since disaster assessment task requires images from pre- and post-disaster phases, statistical radiation normalization was applied to minimize the noise-based radiation difference amongst the multi-temporal images (Biday and Bhosle 2010). The process involves the selection of a clear image as a reference and normalizing the radiation values of other images by using statistical characteristic quantity of reference image, such as gray mean, standard deviation and gray variation. This results in parity in the radiation scale between the reference image and the target images (Chen, Vierling and Deering 2005). An elaboration of the processes can be found in Zheng et al. (2019). Therefore, with the assumption that the gray-scale image obeys Gaussian distribution statistics, the following radiation-normalization model was applied:

$$g_p = \left(\frac{g_t - \mu_t}{\sigma_t} \times \sigma_r \right) + \mu_r \quad (1)$$

where g_p is the pixel gray value after normalization of target image; g_t , μ_t and σ_t are the pixel gray value, mean value and standard deviation of the target image, respectively; and σ_r and μ_r are the mean value and standard deviation of the reference image, respectively.

In this paper, cloud free stable composite image of January month 2020 was used as reference images. 22 May 2020 was the new moon day. After the application of normalization, the root-mean-square error of corrected target images and reference image was reduced, indicating effective reduction in noise.

Fig. 2 **a** Population density (persons/hectare) of the study area and **b** distribution of crop land in the study area

Table 1 Details of data used in the study

Data name/specification	Time	Data source
Daily NTL data (spatial resolution 750mts)	17 May 2020, 22 May 2020 and 23 May 2020	NASA/NGDC, Suomi NPP_VDNES_L1 Accessed 24 May 2020. https://landsweb.modaps.eosdis.nasa.gov/search
Monthly cloud free NTL data (spatial resolution 750mts)	January 2020	Earth Observations Group (EOG). Average radiance composite images. Accessed 04 June 2020. https://eogdata.mines.edu
Cyclone 'AMPHAN' path	20 May 2020	Cyclone Warning Division, Office of the Director General of Meteorology, India Meteorological Department, Ministry of Earth Sciences. Accessed 22 May 2020. https://mausam.imd.gov.in/imd_latest/contents/cyclone.php# ; and Accessed 14 June 2020. https://mausam.imd.gov.in/Forecast/marquee_data/Summary%20Super%20Cyclonic%20Storm%20Amphan%20(13062020).pdf
Population data (Spatial resolution 100mts and estimate the number of persons per square.)	2019	WorldPop (www.worldpop.org)—School of Geography and Environmental Science, University of Southampton; Department of Geography and Geosciences, University of Louisville; Departement de Geographie, Universite de Namur) and Center for International Earth Science Information Network (CIESIN), Columbia University (2018). Global High Resolution Population Denominators Project—Funded by The Bill and Melinda Gates Foundation (OPPI134076). Accessed 24 May 2020. https://dx.doi.org/10.5258/SOTON/W/P00645
Land use /land cover Map (1:50,000)	2015–16	LULC, 50 K, West Bengal, BHUVAN Thematic Services, National Remote Sensing Centre, Hyderabad. Accessed 04 June 2020. https://bhuvan-app1.nrsc.gov.in/thematic/thematic/index.php

2.4 Reliability of NTL data to population estimation

Several studies have used *coefficient of determination* (r^2) to measure the strength of relationship between population and NTL data, and it is found to be relatively accurate and easy to implement (Zhuo et al. 2009; Zheng et al. 2019). ‘ r^2 ’ between two quantitative variables, x and y , measures how well the variation in one variable, x , explains the variation in the other, y . This is best explained by Pearson correlation coefficient (r) and the best-fit regression model. In order to quantify the reliability of corrected NTL data to the population, a linear regression analysis was conducted between district-wise NTL density (17 May 2020 NTL data) and district-wise population density (Population 2019 data), where NTL Density was calculated as:

$$\text{NTL Density} = \frac{\sum R_i}{A_i} \quad (2)$$

where R is NTL radiance value and A is area.

2.5 Assessment of power outage extent and intensity for delineation of crisis zones

Power outage extent can be visually interpreted from a false colour composite image, which can be produced by combining the statistically radiation normalized pre-event data for 17 May 2020 and post-event data for 22 May 2020 and 23 May 2020. Specifically, the pre-event lights (17 May 2020) are assigned to red colour intensity, green colour for 22 May 2020 and blue intensities used for 23 May 2020. The composite quickly highlights power outages through the resulting colour combinations.

The intensity of power outage can be calculated from the ratio between the normalized post-disaster NTL radiation, 23 May 2020, and the normalized pre-disaster NTL radiation, 17 May 2020 (Cole et al. 2017; Wang et al. 2018). This NTL ratio (R_{NL}) can be expressed as:

$$R_{NL} = \frac{NTL_{\text{post-disaster}}}{NTL_{\text{pre-disaster}}} \quad (3)$$

where $NTL_{\text{post-disaster}}$ is the total NTL radiation after a disaster and $NTL_{\text{pre-disaster}}$ is the total NTL radiation before a disaster.

As shown by Eq. (3), the greater the reduction in NTL post-disaster, the smaller the value of R_{NL} will be. Since the brightness of the NTL reduces after the disaster representing power outages, the R_{NL} is basically greater than zero, and the power outage areas will have pixel values ranging between zero (0) and one (1). The generated R_{NL} intensity was divided into three levels of ‘crisis zones’ based on histogram distribution as: high, moderate and low. The output was finally validated with the false colour composite image.

2.6 Determination of the affected population and cropland area

The crop land spread map of the study area was extracted from the land use/land cover map downloaded from Bhuvan portal. In this study, the ‘crop land’ includes cultivable lands, agriculture plantation and land under orchards and horticulture. For the

generation of affected population and crop land area, the generated crisis zones and crop land area data layers were resampled at 100 m spatial resolution equivalent to the population 2019 data layer by ‘nearest neighbour’ algorithm. Using spatial analysis tools, the area of district-wise crisis zones and crop land area for each district under different crisis zones were calculated. Using the zonal statistics, crisis zone-wise population total for each district within the study area was computed as:

$$P_e = \rho_e \times N_e \quad (4)$$

where P_e is the total population affected in each zone, ρ_e is the population in the affected pixels, and N_e is the number of affected pixels under each crisis zone.

In addition, the proportion of the crisis zone-wise affected area, population and cropland were also obtained by using the total geographical area, the total population and total cropland area, respectively, for each district in the study area.

3 Result

3.1 Relationship between NTL data and population

An extremely strong correlation between NTL density and population density with r^2 value of 0.996 was achieved (Fig. 3a). The possible reason for such strong correlation can be the Kolkata district. Being a megacity, Kolkata has both very high population density and high NTL intensity when compared to the rest of the study area, and this may influence the correlation outcome. Therefore, another *coefficient of determination* was computed considering the same variables, but excluding Kolkata district. The resultant r^2 again shows that a very strong correlation of 0.867 between NTL Density on 17 May 2020 and population density of 2019 exists (Fig. 3b), which confirms that NTL data truly represent the population distribution of the study area.

Fig. 3 Correlation between NTL density and population density: **a** with Kolkata district, and **b** without Kolkata district

3.2 Identification of power outage extent due to the cyclone

A false colour composite image was produced by combining nearly cloud free, pre- and post-event data for 17 May 2020, 22 May 2020 and 23 May 2020 following the supercyclonic storm ‘AMPHAN’ (Fig. 4). Lights that remained lit throughout the event appear in all the dates and are assigned nearly equal values to each pixel in all three scenes, resulting in a white colour. Lights present in the pre-cyclone imagery but missing or dimmed in the post-event imagery (both on 22 and 23) appear in red colour. The places where lights were missing till 22 May appear in pink colour as explained from the colour composite index. The southern most districts of the study area, around Kolkata Metropolitan Area and Haldia town, are the most cyclone affected parts.

Fig. 4 False colour composite of pre-event (17 May 2020) and post-event (22 May 2020 and 23 May 2020) imagery from Suomi-NPP VIIRS Suite DNB data used to identify possible power outage areas due to Cyclone ‘AMPHAN’. White shades indicate points where lights are present in both the pre- and post-event imagery, while red areas suggest reduced light intensity in the post-event images

3.3 Delineation of crisis zones

The R_{NL} values representing power outage intensity due to cyclone ‘AMPHAN’ were calculated from the ratio between 23 May 2020 and 17 May 2020 NTL radiation. From the generated R_{NL} range, three categories of ‘crisis zones’ indicating the severity of cyclone damage were: high crisis zone ($R_{NL} < 0.45$), moderate crisis zone ($0.45 > R_{NL} < 0.9$) and low crisis zone ($R_{NL} > 0.9$). The districts, whose major portions are falling under ‘high crisis zone’, are Kolkata, Haora, North 24 Parganas, South 24 Parganas and East Medinipur (Fig. 5a). Within South 24 Parganas, the Sundarbans—India’s largest Protected Wetland and UNESCO Site—lying in south-eastern part of the district, is falling in the ‘low crisis zone’. Since the region is a very low lit area, there is negligible change in NTL values in pre- and post-disaster scenarios. The R_{NL} value of the Sundarbans is almost 1, which is beyond the high and moderate crisis zone thresholds. The extent of damage due to cyclone ‘AMPHAN’ in and around Kolkata is quite critical with major portions of the district still under dark even after 2 days of the cyclone landfall (Fig. 5b, c). The accuracy assessment of the classified crisis zones was conducted with reference to the three days false colour composite image of the study area. The reliability of the classified output of the crisis zones with reference to the false colour composite image was found satisfactory by achieving an accuracy level of 82%, with Kappa Stat of 0.698.

3.4 Estimation of affected population and crop land

After the delineation of crisis zones, the zone-wise population and crop land affected under all districts were calculated. From Eq. (4), total population affected and further

Fig. 5 Crisis categories: **a** zones of different power outage intensity due to cyclone ‘AMPHAN’; **b, c** variation in radiation intensity in and around Kolkata extracted from the pre- and post-cyclone imagery

the proportion of affected population to the total population for each district were generated. Similarly using the spatial analysis tool, the crop land area was extracted from the land use/land cover map of the study area for all the districts for both high and moderate crisis zones.

The severely cyclone-ravaged areas of the study area are mainly lying within the 50 km buffer of the cyclone path (Fig. 6). Geographical area-wise North 24 Parganas has maximum share of land falling under high crisis zone; however, South 24 Parganas has maximum share of crop land and population under the said zone (Table 1S). More than 80% of district population and crop land area have suffered moderate to high damage in Haora, North 24 Parganas, South 24 Parganas and East Medinipur.

Fig. 6 District-wise estimation of affected population and crop land area under moderate to high crisis zones. Maximum impacted regions are the districts lying within 50 km buffer of the cyclone path. Kolkata District with 100% urban population has no land use under crop land category

4 Discussion

NTL data appear suitable for quantifying the macro-level damage assessment induced by the cyclone ‘AMPHAN’ in West Bengal state, India. The variation of NTLs from very brighter to very dimmed or no lights represents the areas that were heavily damaged by the cyclone. The decline in average brightness between the pre- and post-disaster phase was seen in both urban and rural areas. This study also assesses the affected population and the affected crop land area retrieved from changes in NTL data caused by the cyclone disaster. Since the cyclone passed over the populous parts, the total moderate to highly affected population as retrieved from the NPP-VIIRS DNB data is approximately 56 million, which is nearly 70% population of the study area. The cyclone ‘AMPHAN’ had its landfall in South 24 Parganas; hence, it is the only district where more number of population is under high crisis zone than in moderate crisis zone. Similarly about 66% of the crop lands of the study area were found to be affected by the cyclone, with most affected districts being North and South 24 Parganas. The cropping intensity of West Bengal is more than 180% (DoA 2016), and the standing crops during the month of May are boro paddy, sesamum, jute, maize, nuts, mango fruit and horticulture crops like betel plantation, flowers and vegetables. With the outbreak of the novel coronavirus-caused COVID-19 in India, as part of global pandemic, agriculture is the only sector upon which the state’s economy depends, and destruction of standing crops by the cyclone is a huge economic loss for the state.

Application of NTL data for disaster damage mapping is still in infancy in India. The earlier studies have majorly used NTL data as a measure of economic activity (Beyer et al. 2018; Prakash et al. 2019), rural electrification (Burlig and Preonas 2016; Dugoua et al. 2018), electricity consumption pattern (Chand et al. 2009), urban dynamics (Roy Chowdhury et al. 2010; Pandey et al. 2013) and predicting poverty (Subash et al. 2018). Till now in India, NTL data have been found to be exploited in a very limited way from disaster perspective (Badrinath et al. 2011; Zhao et al. 2018a). Supercyclonic storm ‘AMPHAN’ is declared as the costliest tropical cyclone, with reported economic losses in India of approximately US\$14 billion, on record for the North Indian Ocean (WMO 2020). The present study, therefore, was an attempt to assess the spatial distribution of damage done by the cyclone, which is first of its kind using NPP-VIIRS DNB data in this region.

The study has found that NPP-VIIRS DNB data can provide targeted data support for rapid assessment and timely decisions towards the management of cyclone disasters, except for certain limitations. Such limitations may arise in mainly two conditions (Zhao et al. 2018a): a. cyclones are often accompanied by heavy rain and cloud cover, so getting an immediate clean post-disaster image is often difficult; and b. the NPP-VIIRS DNB data are not suitable for areas with relatively low NTL intensity, such as the case of Sundarbans where settlements are of rural character, very small in size and highly scatter. Therefore, the analysis may have missed certain portions of the affected population due to very low NTL values.

5 Conclusion

Cyclone AMPHAN has caused grave damage to essential infrastructure and services in cyclone-ravaged areas of West Bengal. The present study has quantitatively assessed the extent of damage caused by the cyclone, in view of the population and crop land area. In

the absence of any detail official assessment report in public domain on the extent of damage till date, ground verification of the present assessment is not possible. However, the findings of this study match with the damage estimates published by various news agencies from time to time. Therefore, NTL derived from NPP-VIIRS DNB data was found suitable to highlight the affected regions due to the cyclone. High correlation between VIIRS NTL data and population was found to be a good fit for a broad analysis like this. However, its application was found limited to the areas where the lighting facilities are inadequate. Sundarbans in South 24 Parganas, the world's largest mangrove forest, is one such area where the true picture of coastal damages including breached embankments, could not be captured. Beyond such limitations in contrast to ground surveys, which takes time and substantial financial outlays, the freely available NTL data that are placed in the public domain with a very short lag, come as a relief for rapid damage assessment caused by disasters. This paper has demonstrated a simplified approach to conduct a post-disaster damage assessment, which can be potentially useful for disaster managers for generating first hand information where immediate complementary data are difficult to collect.

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Compliance with ethical standards

Conflict of interest The author declares no conflict of interest.

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