Geospatial Modelling of Post-Cyclone Shaheen Recovery using Nighttime Light Data and MGWR

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Abstract

Tropical cyclones are a highly destructive natural hazard that can cause extensive damage to assets and loss of life. This is especially true for the many coastal cities and communities that lie in their paths. Despite their significance globally, research on post-cyclone recovery rates has generally been qualitative and, crucially, has lacked spatial definition. Here, we used freely available satellite nighttime light data to model spatially the rate of post-cyclone recovery and selected several spatial covariates (socioeconomic, environmental and topographical factors) to explain the rate of recovery. We fitted three types of regression model to characterize the relationship between rate of recovery and the selected covariates; one global model (linear regression) and two local models (geographically weighted regression, GWR, and multiscale geographically weighted regression, MGWR). Despite the rate of recovery being a challenging variable to predict, the two local models explained 42% (GWR) and 51% (MGWR) of the variation, compared to the global linear model which explained only 13% of the variation. Importantly, the local models revealed which covariates were explanatory at which places; information that could be crucial to policy-makers and local decision-makers in relation to disaster preparedness and recovery planning.

Keywords: Post-Shaheen Cyclone Recovery, GIS, MGWR, Night Time Light NTL Data, Community Resilience

1. Introduction and theoretical background

Tropical cyclones are destructive natural hazards that affect coastal areas in tropical regions, commonly leading to long-lasting catastrophic impacts on physical, socioeconomic and environmental assets, and loss of life. Cyclone impacts affect both the private and public sectors, particularly the transport, education and business sectors. The intensity of the impacts and recovery rates vary from place to place due to local variations in community resilience and each population's ability to adapt to, and cope with, cyclone stressors (Xu & Qiang, 2021; Adger, 2000).

Cyclone recovery, as a process, can be defined as the effort, support and assistance given to local communities during and after a disaster to achieve the states of reconstruction and rehabilitation quickly, and to rebuild any damaged infrastructure (Islam & Walkerden, 2014; Quarantelli, 1999; Oloruntoba et al.,2018;). During post-disaster, the cyclone recovery stage is crucial in terms of revitalising the local economy and building the resilience of local communities, particularly in reconstructing destroyed houses, replacing damaged infrastructure and facilities, and restoring daily services fully (Labadie, 2008; McEntire, 2012; Gaillard et al., 2019).

Across communities that lack vigorous capacity planning and metrics, assessment of post-disaster recovery progress is often quite challenging (Horney et al.,2018). Adaptive capacity is associated with the recovery process, and it refers to a local community's capability to handle a cyclone's most destructive components; predominantly storms, precipitation and high velocity winds. Similarly, the degree of modification and confrontation to cyclone risk is a crucial determinant of recovery and adaptation opportunities (Astill, 2017). The most relevant and effective sources of capacity are assets, governmental polices, civil defence facilities, cultural knowledge, social organizations and local solidarity networks (Uddin et al., 2020). Moreover, community capacity includes households' abilities to utilise, exploit and benefit of these resources to cope with disaster impacts and reconstruct damaged assets and infrastructure (Gaillard, 2010).

Spatially, cyclone recovery can be defined as the ability of each local community to restore and rebuild livelihoods and production systems to normal levels pre-disaster (Udden et al., 2021). Temporally, the period of recovery may also vary according to the nature of the economic sector. For example, after a cyclone agricultural activity may take months or even years to be reconstructed and restored (Handmer & Hillman, 2004; Chhotray & Few, 2012). In contrast, the recovery progress and levels may be generally high in urban communities that are resilient and well-prepared compared to deprived urban agglomerations and rural areas.

Seeking to facilitate a community of practice for modelling disaster recovery, Miles et al., (2019) suggested to increase the participation of all hazard researchers and modellers in disaster recovery research. This would be an effective strategy to enrich resources, tools and techniques of studying, modelling and simulating disaster recovery particularly datasets, documentation, and programming libraries. Conducting a literature survey of disaster recovery, Horney et al., (2017) developed a guiding framework of disaster recovery indicators following the Federal Emergency Management Agency (FEMA)'s Recovery Directorate in the United States (US). The findings specified that the majority of recovery indicators were well constructed and represented which supports post-disaster research and planning of management and mitigation. Similarly, and using very high-resolution satellite images, Brown et al.,2008 developed a suite of indicators that enable monitoring and assessing rapid post-disaster recovery and physical rehabilitation. These remote sensing indicators involves various natural, environmental, and socioeconomic factors that are integrated in a reliable and effective tool of recovery assessment.

Satellite sensor images, combined with other spatio-temporal data have been shown to be effective inputs for cyclone damage assessment. Previous studies have been largely restricted to non-spatial analysis of the economic impacts of cyclones (Hsiang & Jina, 2014; Moniruzzaman, 2019; Zhou & Zhang, 2021) and the variable impacts on different land covers (Chen et al., 2013; Moatty et al., 2021; Shamsuzzoha et al., 2021). Recent studies have established the importance of incorporating geospatial techniques and satellite sensor imagery in cyclone damage assessment. For example, Jaman et al. (2021) employed satellite microwave imagery, as well as GIS-based multi-criteria analysis (MCA), to assess cyclone damage at a fine geographical resolution (village level) at Bhadrak district in Odisha State, India. The findings indicated substantial spatial variation in cyclone impacts and damage, particularly in the socioeconomic and environmental sectors. These spatial differences were attributed mainly to disparities in vulnerability and exposure across the study area. In another example, Cortés-Ramos et al. (2020) analysed the impacts of tropical cyclones on the southern tip of the Baja

California Peninsula, Mexico. Landsat 8 and MODIS images were used and several spatial indices were calculated to assess cyclone damage spatially; specifically vegetation damage. The results showed that there were high spatial variations of the severe damages caused by high velocity wind and intense rainfall. Likewise, Ahammed & Pandey (2021) provided a comprehensive assessment of the damage caused by cyclone *Amphan* during 15–21 May 2020 to West Bengal and Odisha states in India. They found that green cover and croplands were the most severely damaged, being affected by the cyclonic surge and heavy precipitation.

In another foundational work, Stevenson et al., (2010) investigated the spatial variations of recovery from Hurricane Katrina across coastal Mississippi. Utilizing building permits and other statistical data, they found spatiotemporal variations of building environment recovery and the recovery rates were associated with damage levels as well as housing density and concentration. In assessing the same post-recovery Hurricane Katrina, Abramson et al., (2010) adopted confirmatory factor analysis using five measures of social role adaptation, mental and physical health, economic and housing stabilities. Overall, all the indicators were significantly associated with the developed latent measure of recovery while social and health measures indicated higher associations.

Monitoring spatiotemporal changes of dynamic phenomena and events on the Earth's surface is crucial, particularly for planning and alleviating the effects of natural hazards and risks (Doll et al.,2006; Zhao et al.,2018; Shi et al.,2020). Geospatial techniques and remote sensing images have been employed extensively as effective instruments to monitor human activities and environmental changes on the Earth's surface (Du et al., 2014; Li et al., 2016). Night-Time Lights (NTL) data in particular have great potential for spatial analysis and modelling of human activities, physical dynamics and interactions between the two (Bennett & Simth, 2017; Alahmadi et al., 2021a; Alahmadi et al., 2021b). Night lights (and the consequent electricity consumption) can be used as an indicator and proxy for community socioeconomic development and wellbeing (Elvidge et al., 2012; Ghosh et al., 2013; Mann et al., 2016; Mohan & Strobl, 2017). With this argument, and over the post-disaster stage, few studies used NTL data and geospatial techniques have been developed to quantify and assess cyclone damage, community resilience and recovery spatially (e.g., Román et al., 2019; Qiang et al., 2020; Xu & Qiang, 2021; Sarkar, 2021). However, these studies are limited by the lack of adopting geospatial modelling approaches to estimate spatial variations of recovery rates across small neighbourhoods.

Due to its location along three major water bodies (the Arabian/Persian Gulf, the Sea of Oman and the Arabian Sea), Oman is the most prone country to tropical cyclones amongst the countries of the Arabian Peninsula. With a long coastline (3165 km) stretching from Musandam in the far north to the administrative boundaries of Yemen in the south-west, the Omani coastal communities are exposed to devastating cyclones. Historically, and over the last century up to 2021, the coastal areas of Oman were hit by several cyclones that caused asset damage and fatalities. For example, in 1898, a devastating cyclone hit the east and northeast coasts and made landfall. Reported information about this cyclone and its destructive impacts is limited. However, its path was recorded as from the Arabian Sea moving over Al-Wusta and Al-Dakhliya governorates towards the middle of the Al-Batnah coastal plain (Mansour et al., 2021). More recently, in 2007, the intense cyclone Gonu struck the northeast coast of Oman. The cyclone was considered as the nation's worst disaster and the most memorable catastrophe in the Omani social (collective) memory. The cyclone caused 50 deaths and widespread damage and destruction impacting coastal populations, majorly in the Muscat and North Al-Sharkiya governorates. The total economic loss was estimated to be approximately $ 4.2 billion and, in the recovery phase, it took a long time to reconstruct damaged infrastructure and rehabilitate affected communities (Tyagi et al.,2011). In 2010, cyclone Phet developed over the Arabian Sea and passed towards the northeast coast of Oman causing heavy rainfall (600 mm) and high velocity winds that affected households and infrastructure in the low lying-lands of the east Muscat Wilayats, particularly Qurayyat. Cyclone Phet caused 24 fatalities and significant damage estimated at $780 million (Rahimi et al., 2015).

Cyclones frequently hit not only the north and northeast Omani coasts, but also the south and southeast low lying-lands within Al-Wusta and Dhofar governorates. In May 2018, the southern coasts of Oman experienced the intense cyclone Mekunu which developed over the southwest Arabian Sea and battered Salalah Wilayat causing fatalities and significant damage, particularly to coastal houses, infrastructure and facilities (Mansour, 2019).

On 24th of September 2021, a low-pressure area developed over the Bay of Bengal and the next day the climatic system strengthened into a tropical storm. Later, after three days it moved out from western India into the Arabian Sea and was known as Gulab. While Gulab struck eastern India and had a significant impact on coastal areas, the Shaheen cyclone made a considerable landfall in the northeast coasts of Oman on 3rd October 2021. As an intense circular storm, the Shaheen cyclone was recorded as the strongest tropical storm since the 2007 cyclone Gonu with thunderstorms, storm surges, torrential precipitation (200 to 370 mm), excessive flooding and powerful winds (120 to 140 km h^{-1}). As a result, the cyclone caused 13 deaths, household evacuations (around 5000 households were evacuated to shelters), infrastructure damage, and severe economic losses.

The catastrophic impacts of the Shaheen cyclone occurred predominantly across the coastal areas of Al-Batnah plain, particularly the Al-Khabourah, Al-Swayq, Al-Musanaah Wilayats. Mansour et al. (2021) used geospatial modelling to map the spatial distribution of tropical cyclone risk across the northeast coast of Oman. The final map of the developed risk index was similar to the distribution of the impacts and damage due to the Shaheen cyclone. Despite the fact that areas located in the far east such as Sur wilayat is significantly exposed to storms and cyclones, other coastal Wilayats in the middle and north of Al-Batnah coastal plain, compared to internal Wilayats, are increasingly more exposed and vulnerable to cyclones that develop over the Arabian Sea and Indian Ocean.

Measuring community resilience to, and recovery from, the destructive impacts of cyclones is needed to characterize the spatial variation and distribution of disaster risk (Burton, 2015; N. Lam et al., 2016). Nonetheless, most of the conducted studies rely on qualitative methods and mixed approaches (e.g., Pfefferbaum et al., 2013; Islam et al., 2017; Uddin et al., 2020) and, thus, assessments of human responses and local communities' endeavors to restore normal life often lack measurable and quantitative outcomes at finer spatial resolutions or are completely nonspatial (Cai et al., 2018). The consequences of cyclones, as an extreme climatic event, not only influence the economy of the impacted areas, but also disrupt critical daily services, facilities and infrastructure. Accordingly, assessment of cyclone damage and recovery should be accomplished through quantitative and spatial means.

Despite the growing body of literature surrounding cyclone resilience and recovery globally (e.g., N. Lam et al., 2016; Qiang et al., 2020; Xu & Qiang, 2021; Sarkar, 2021), geospatial modelling of recovery at local and intermediate scales is still rare. Subsequently, this research attempts to bridge this gap by developing a modelling framework of recovery, using the Shaheen Cyclone as a case study. Several topographical, environmental and spatial determinants, as well as one global and two local statistical models, were employed to predict the spatial variation in the cyclone recovery pattern across the northern coasts of Oman.

The principal research aims are as follows:

- The identification of spatial, topographical, and environmental influences on speedy recovery from cyclones.
- The evaluation of possible correlations between geographical variation in recovery and the aforementioned influences.
- The use of NTL data and multiscale statistical modelling to understand the implications of topographical and environmental properties for community resilience.

The current study represents a novel attempt to examine this subject in the context of the Gulf Cooperation Council (GCC) countries and Oman. It employs an innovative modelling framework to evaluate spatial variation in the rate of recovery from cyclones. The significance of this research lies in its potential to assist the development of national preparedness and mitigation strategies, in addition to the provision of critical data related to quantification of the fundamental determinants of achieving rapid post-cyclone recovery at the local level.

2. Materials and methods

2.1 Study area

The study region is located north of Oman and covers an area of 22,924 km^2 that includes 22 Wilayats (states) administered by six governorates, namely: Muscat, Al-Batnah North, Al-Batnah South, Al-Dakhaliya, Al-Sharkya South and Al-Sharkya North (Figure 1). The Muscat governorate (3,796.7 km^2) contains six Wilayats, of which five are coastal. Thus, only the Wilayat of Al-Amrat has no border with the Oman Sea. The governorates of Al-Batnah North (7,899.3 km^2) and Al-Batnah South (5,323.1 km^2) are subdivided into six Wilayats each. These comprise the natural region known as the Al-Batnah coastal plain. Samail and Bidbid are part of the Al-Dakhaliya governorate. In addition, Dama Watayian is located in Al-Sharkya South, whereas Sur is situated in Al-Sharkya North. The four coastal Wilayats of Muscat, Mutruh, Bawshar and Aseeb are located within the Muscat governorate and regarded as urban zones. The remaining administrative units contain a mixture of urban and rural settlements.

The region examined in this research constitutes Oman's most densely populated area. It contains extensive urban cover and a population in 2019 of 2.9 million, thereby representing 62.5% of the entire population of Oman (NCSI, 2019). The region is characterized by socio-economic diversity and the population includes both native inhabitants and migrant workers engaged in the region's various economic, commercial and financial activities. The socioeconomic character of this region makes it vulnerable to the impacts of cyclones.

The coastal plain of Al-Batnah is 1 m above sea level and host to important arable land and livestock farming activities. The physical and topographical characteristics of the northwest section of the study zone, known as the Al-Batnah coastal plain, includes numerous dry valley estuaries that are prone to climatic and natural hazards, not least of which are storm surges, excessive precipitation, flooding and cyclones. This susceptibility is exacerbated by rapid economic growth and urbanization. Economic development in this zone has led to the concentration of disproportionate amounts of Omani capital stocks and assets, thereby rendering it essential that modelling spatial variation in cyclone recovery in exposed areas can guide decision-making and contribute to the formulation of national and subnational readiness strategies, not least for marginal communities that may be less resilient to the impacts of cyclones.

Figure 1. Location of the study area. (Upper panel) light green line indicates the Shaheen Cyclone track. Pink polygons denote built-up areas across the coastal neighbourhoods. Light purple polygons refer to the Wilayat (states) boundaries level.

2.2 Nighttime Light (NTL) Data

The Visible Infrared Imaging Radiometer Suite (VIIRS) was created onboard the Suomi-National Polar-orbiting Partnership (S-NPP). It offers daily data updates regarding the light reflected from the Earth, as recorded by the Day-Night Band (DNB) instrument (Roman et al., 2018). The spatial resolution of the DNB layer is 500 m. In addition, it has a radiometric resolution of 16 bits and a bandwidth range of 500 to 900 nm. The character of the VIIRS/DNB enables measurements to be taken of light from human activities, including road lighting and cars, residential, commercial and industrial structures (Alahmadi et al., 2021a). The National Aeronautics and Space Administration (NASA) also created two Black Marble products (VNP46A1 and VNP46A2) (Roman et al., 2018). The VNP46A2 product underwent additional development with the addition of the bidirectional reflectance distribution function (BRDF) model, designed to diminish the influence of irrelevant nighttime light sources. However, it remained unavailable during the Shaheen Cyclone period of this research. Therefore, the present research relied on the VNP46A1 product for five days, including one day prior to the 5 September 2021 cyclone and four days following the cyclone. Hence, it included the period 4 October to 7 October 2021.

2.3 Method

2.3.1 NTL image processing

The current research adopted five NTL images, each of which was processed separately to generate first-rate NTL images that could be used to compare the situation prior to, and following, the Shaheen Cyclone. The processing comprises two stages, as follows:

A) First-rate NTL pixels: The raw VNP46A1 product is influenced by multiple atmospheric variables, including clouds, moonlight and snow. These influences can alter authentic artificial light radiance (Roman et al., 2018). For this reason, the data require additional processing. Information pertaining to the NTL pixels is incorporated within the QF Cloud Mask. This includes data about times, cloud quality, cloud confidence, shadow and ice, all of which are employed to improve the DNB layer, thereby generating superior data. Only NTL pixels coded as confident clear (00) in the confidence indicator layer and medium (10) and high (11) in the cloud mask quality layer were used in the analysis (Yin et al., 2021). Subsequently, the Moon Illumination Fraction layer was deducted from the DNB layer (Anand & Kim., 2021).

B) Low brightness NTL intensity: Unpopulated areas, including those that are predominantly bare or covered with vegetation, tend to reflect comparatively limited NTL intensity values, which can impact the overall findings across substantial administrative boundaries (Alahmadi et al., 2021b). Consequently, 5 September 2021, which was the day before the cyclone struck, was employed to filter the low radiance values. A trial-and-error method was adopted, wherein a radiance value of 5 $nWcm^{-2}sr^{-1}$ was utilised to eliminate unpopulated NTL pixels, in addition to establishing a preliminary mask capable of filtering low radiances in the post-cyclone period. Subsequently, a binary mask was created for each day (5 September 2021 and 4-7 October 2021). The masks were superimposed to produce one mask that was then multiplied for each day. This stage was designed to create an equal number of NTL pixels for each day.

C) Computing the percentage difference: After applying the above processing steps on each day, all the raster and vector data were projected using the Albers Equal Area projection (Alahmadi et al., 2021b). The sum of the radiance values was computed at the eastern, subnational and neighbourhood zones. The percentage difference of the NTL values was calculated as follows:

$$NTLPD_i = \left(\left(\frac{TNTL_i - RNTL_i}{RNTL_i}\right) \times 100\right) \qquad (1)$$

Where $NTLPD_i$ denotes the NTL percentage difference (subnational and neighborhood zones) and $TNTL_i$ are the sum of the radiance values of the target (October 4 to 7, 2021) while $RNTL_i$ refers to the NTL values in the reference day (September 5, 2021). Low NTLPD values are here assumed to indicate slower recovery rate while high values signify higher recovery. For instance, large values of NTL show greater community resilience and high socioeconomic recovery whilst low values imply the delay in the reconstruction of physical infrastructure and restoration of normal life.

2.3.2 Global and local modelling techniques

Global regression modeling

Ordinary Least Squares (OLS) regression is typically employed to link response variables to predictors or explanatory variables. To estimate the parameters, the sum of squares is minimized. From a spatial perspective, the model operates according to the presumption that there is a predictable and unchanging relationship across the entire study zone. For this reason, it is possible that the implied independence expectations linked to the relevant spatial information could be inappropriate (Hutcheson, 2011; Pohlman & Leitner, 2003). The correlation coefficient between the dependent variable

(y) and a set of independent variables (x_1, x_2, ….. x_n..) is then provided. The global OLS regression model is given as follows:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_n x_n + \varepsilon \qquad (2)$$

where y_i comprises the response variable observation (recovery rate) at the $\boldsymbol{i}$th locations (neighbourhoods), $\boldsymbol{\beta_0}$ denotes the intercept and β_1 indicates the parameter estimate for x_1. x_n represents the set of explanatory variables, and ε signifies the residual error term.

The variance inflation factor (VIF) was adopted to check for any multicollinearity. Overall, for every independent variable, where the VIF value exceeded 10 for any independent variable, this was deemed to be indicative of an issue with the model specification. Hence, such variables were eliminated (Montgomery et al., 2021). The VIF factor is represented as:

$$VIF_I = \frac{1}{1 - R^2{}_i} \qquad (3)$$

where VIF refers to the variance inflation factor while R^2 signifies the coefficient of determination.

Local regression modeling

Geographically Weighted Regression (GWR)

The global OLS regression model is spatially stationary in its parameters. Hence, it is limited to the modelling of correlations between cyclone recovery (the response variable) and predictors (environmental, topographical, and spatial variables) with no consideration of the effect of geographical variation in the relationship (Brunsdon et al., 1996; Fotheringham et al., 1998). In contrast to the global regression model, GWR is spatially non-stationary. For this reason, it can be employed to model relationships that fluctuate spatially. This means that the model can search for spatial heterogeneity and calculate individual local parameters for each zone (Brunsdon et al., 1996; Fotheringham et al., 1998; Charlton et al., 2009). The GWR model can be represented in accordance with Fotheringham et al. (2003):

$$\mathrm{y}_i = \beta_{0i}(u_i, v_i) + \sum_{n=1}^{k} \beta_{ni}(u_i, v_i) x_{ni} + \varepsilon_i \qquad (4)$$

where y_i denotes the cyclone recovery at a given location or neighbourhood i, (u_i, v_i) signifies the centroid of zone (neighbourhood) i, β_{0i}, β_{ni} represent the intercept and influence of variable n for zone i, respectively, x_{ni} represents the values of the *ith* independent variables, and ε_i is a random error term. The matrix form is written as per Fotheringham and Oshan (2016):

$$\hat{\beta}(i) = (\,\boldsymbol{X}'W(i)X)^{-1}\,\boldsymbol{X}'W(i) \qquad (5)$$

where $\hat{\beta}$ specifies the vector of parameter estimates ($p \times 1$), $\boldsymbol{X}$ denotes the matrix of the predictor variables ($n \times p$), $W(i)$ encompasses the spatial weights matrix ($n \times n$), and y signifies the vector of observations of cyclone recovery (p×1). The matrix $W(i)$ is created from the weights of each zone (neighbourhood) in accordance with the distance between the matrix and the location i. The Gaussian and bisquare weighting kernels are typically used to allow neighbourhoods in proximity to i to exercise a more significant impact on the estimation of $\beta_{ni}(u_i,v_i)$ than is possible for neighbourhoods situated at a greater distance from i. Both the bandwidth and kernel function require quantification when the bandwidth is ascertained in accordance with the Euclidean distance and number of proximate neighbours. Multiple diverse bandwidths can be tested to determine the optimal neighborhood type from which to produce the local weighting (Mollalo et al., 2020).

Multiscale Geographically Weighted Regression (MGWR)

GWR is able to identify variation in parameters spatially. However, it assumes that spatial scale is constant. A fixed spatial scale may be inappropriate when spatial properties encompass multiple complex processes with diverse spatial scales. In contrast to GWR, MGWR is not dependent on the rigid assumption that all properties exhibit a comparable, single spatial scale. In other words, MGWR permits differences in the spatial values for localized regressions in respect of their variables. Therefore, spatial variation can arise in the link function between the response variable and explanatory variables, in addition to various scales that include different bandwidths across the surface of the study zone (Fotheringham et al., 2017; Yu et al., 2019; Mollalo et al., 2020). Furthermore, the MGWR model is superior to GWR in several respects, the first of which is that it has the ability to reliably indicate spatial heterogeneity. It can also reduce collinearity and decrease bias in the parameter estimates (Oshan et al., 2019; Wolf et al., 2018). The MGWR model can be represented as:

$$y_i = \sum_{j=0}^{m} \beta_{bwj}\, x_{ij} + \varepsilon_i \qquad (6)$$

where β_{wj} indicates the bandwidths that are employed to adjust the jth conditional relationship (Fotheringham et al., 2017).

3. Results

3.1 Spatial patterns of NTL changes and cyclone recovery

Figure 2 shows the sum of the NTL intensities over the northeast coast of Oman before and after the Shaheen Cyclone. On September 5, 2021 the sum of the NTL intensities was c. 245,000 $nWcm^{-2}sr^{-1}$. This value decreased by 40% to c. 158,000 $nWcm^{-2}sr^{-1}$ on October 4, 2021 as a result of the Shaheen Cyclone, which hit the Sultanate of Oman on October 3, 2021. The Omani authorities took a set of measures to mitigate the effects of this disaster and return eventually to normal life. These measures contributed to an increase in the sum of NTL intensities through October 5-7, 2021 to c. 180,000, 190,000 and 211,000 ($nWcm^{-2}sr^{-1}$), respectively, in comparison with October 4, 2021 (c. 158,000 $nWcm^{-2}sr^{-1}$).

Figure 2 Sum of NTL radiances for different days at the east part of Sultanate of Oman.

The spatial variation in NTL was used as a proxy to measure local community resilience and recovery. Figure 3 illustrates the percentage difference in the NTL brightness spatially during the 4 days after the Shaheen cyclone across the northeast coasts of Oman. In the second day of the cyclone (4th Oct.) the east of Muscat Wilayats, particularly Barka, Musanaah, ASuwayq and Al-Khabourah, exhibited large NTL disturbances and low rates of recovery. In fact, these Wilayats (specifically coastal neighbourhoods and settlements close to the coasts) are highly populated and characterised by a high density of infrastructure and service facilities. Similarly, NTL disturbances were predominantly observed in the western part of Sur wilayat in the far east. Additionally, on 5th October (the third day of the cyclone), although there was a pronounced pattern of recovery across the internal parts of the impacted Wilayats, coastal neighbourhoods in Musanaah, ASuwayq, and Al-Khabourah experienced a large decrease in NTL. The majority of settlements and neighbourhoods in the east Muscat governorate and the west of Al-Batnah plain (e.g., Bowsher Al-Seeb, and Barka) recovered to pre-disaster conditions. Likewise, and during the fourth day of the Shaheen cyclone, the large NTL disturbances continued predominantly in the ASuwayq settlements, and several areas within the surrounding Wilayats continued to show a significant decrease in NTL, particularly across Al-Khabourah in the west and

Musanaah in the east. In these areas, coastal settlements did not recover to their normal conditions during the four days post the cyclone and had large reductions in NTL at both the pixel and neighbourhood levels. Conversely, the lower rates of disturbances and changes in NTL were found primarily in the north west within Sohar and Liwa Wilayats, as well as in Al Amrat in the east of Muscat governorate.

The hazards brought by the Shaheen cyclone in 2021 included intense rainfall and strong winds. The cyclone was responsible for significant damage to homes, farms, businesses and public infrastructure, particularly across the Wilayats of Al-Batnah coastal plain. To assess spatially post-disaster recovery and resilience, we aggregated the NTL values to the Wilayat administrative level.

Figure 3 Rapid recovery rates across the northeast coasts of Oman after the Shaheen cyclone at pixel level (500 m). The percentages in the legend denote the differences in the NTL and were calculated based on equation 1.

Figure 4 depicts the spatial variation in NTL decreases and disturbances at the subnational geographic scale. The centrally located Wilayats in Al-Batinah coastal plain (ASuwayq, Musanaah and Al-Khabourah) were the most impacted areas of the cyclone and, thus, showed the largest NTL reductions (80% to 90%). Indeed, the large proportion of the population who work in agriculture and fisheries is situated disproportionally in these Wilayats. The most damaged/impacted Wilayats are located in the central and northern parts of the coastal plain. A more extensive pattern of NTL disturbances can be observed across the coastal Wilayats located in the middle part of the plain. During 5th Oct., the built-up areas of these settlements continued to show the largest NTL decreases, particularly in ASuwayq and Al-Khabourah (almost 80% to 85% of nightlight disturbance).

Figure 4 NTL reductions (%) across northeast coasts of Oman after the Shaheen cyclone (at subnational administrative zones scale).

In contrast, the west of Al-Batnah Wilayats (e.g., Sohar and Shinas) as well as the east of Muscat (e.g., Qurayyat) demonstrated high levels of recovery and low rates of NTL disturbances (less than 20% reduction). As the Shaheen cyclone passed through the middle part of the plain, Wilayats in the North Al-Batnah governorate experienced the greatest damage and the lowest rates of recovery. During 6th and 7th Oct. all Wilayats showed the same patterns of nightlight reductions and recovery where the central places exhibited large disturbances (60% to 70%). Conversely, urban and rural areas in the northern Wilayats experienced the least damage and, thus, displayed rapid recovery, particularly Shinas, Liwa and Sohar. During the 5 days after the cyclone, ASuwayq wilayat continued to show the lowest rate of recovery and the largest percentages of nightlight disturbances and reductions. This can be attributed to the passing of the cyclone eyewall over this Wilayat.

Figure 5 shows the differences in NTL values before, during and after the cyclone. The plot in the top panel depicts the spatial variation in NTL values where there was a significant decrease in the central part (pixels 200 to 350). Similarly, populated settlements in the east, particularly within Musanaah Wilayat, experienced a large decrease in NTL (pixels 500 to 600). Figure 5 reveals that the NTL decreased most across the central and the eastern parts of Al-Batnah coastal plain. These places are the most intensive urban and rural areas of socioeconomic activities in northern Oman and outside the Muscat governorate. As these places are located in the path of the cyclone eyewall, they witnessed significant impacts on socioeconomic activities. Consequently, the intensity of night time lights in these areas experienced the most obvious decrease during the four days of the cyclone. In the neighbourhoods of ASuwayq, Musanaah and Al-Khabourah Wilayats, the NTL decreased by more than 80% on the first day and by more than 70% on the second day, while the NTL decreased by more than 60% by the fourth day. Examining the spatial structure of the NTL dynamics, the rates of recovery and normal life restoration increased in the west and east parts where the impacts of windstorms and intense rainfall disturbances on infrastructure and built-up areas were smaller. For example, most neighbourhoods of Muscat governorate experienced a small reduction in NTL, while most coastal neighbourhoods of the west part of North Al-Batnah governorate experienced a significant decrease in NTL according to its proximity to the cyclone eyewall and short distances to the cyclone track.

Figure 5 Cross-section illustrating the spatial variation in NTL values across the impacted coastal neighbourhoods before, during, and after the Shaheen cyclone.

3.2 Modelling cyclone recovery

To explore the relationships between NTL-based recovery rates and a set of explanatory spatial factors, linear regression was applied to the whole study area. The global model is a suitable approach for characterising the fundamental associations between NTL-based cyclone recovery and these spatial factors across the impacted coastal area. Accordingly, a range of topographical, climatic and other spatial variables were included in the regression model to determine which factors have an impact on cyclone recovery. Figure 6 illustrates the distribution of the dependent variable (cyclone recovery rate) across neighbourhoods while Figure 7 shows the spatial distribution of the explanatory variables. These variables include distance to cyclone track, elevation, distance to defence centre, distance to shelters, slope, vegetation density, distance to valleys and distance to coastline. Table (1) illustrates the outcome of the global model. The regression coefficients of four variables (coastline, civil defence, elevation and cyclone track) were highly statistically significant (p-values < 0.005). The variance inflation factor (VIF) was used as an indicator of multicollinearity. Characteristically, a VIF value of greater than 10 demonstrates severe collinearity (Kennedy, 2003). The VIF values of all regressors indicated low multicollinearity (VIF <1.5).

Figure 6: Distribution of the cyclone recovery rate (the dependent variable in the regressions) within: (a) NTL pixel base (b) NTL pixels aggregated to neighbourhoods.

Figure 7 the significant independent variables of cyclone recovery: (a) distance to coasts (b) distance to defense centers (c) elevation and (d) distance to cyclone track

Table 1 Comparison of goodness-of-fit parameters for the global and local models.

Criterion	OLS	GWR	MGWR
R^2	0.137	0.427	0.506
Adj. R^2	0.131	0.378	0.461
AICc	2305	2091	1971

Three of the parameter estimates were negative (distance to coastline, distance to civil defence centres and distance to cyclone track) while the positive coefficient for elevation indicates primarily that an increase in elevation is related to an increased rate of recovery. The coefficient estimates also indicated that elevation was the most influential variable, followed by cyclone track and distance to civil defence.

The regression model exhibited a small adjusted R^2 (0.13) indicating that a very large percentage (87%) of the spatial variance in cyclone recovery across the coastal zones remains unexplained and is caused by unspecified covariates (Table 2). The OLS model, which is spatially stationary, is not sufficient to characterize the underlying relationship between the dependent variable and covariates. Therefore, a spatially non-stationary local model was fitted.

Table 2 Parameters of the global model (OLS)

Covariate	Coefficient	Std Error	t-Statistic	Probability	VIF
Intercept	-41.08	3.72	-11.05	0.000000*	
Coastline	-0.00037	0.000088	- 4.24	0.000030*	1.34
Civil defence	-0.021	0.00044	5.99	0.000000*	1.08
Elevation	3.41	0.34	9.93	0.000000*	1.28
Cyclone Track	-0.027	0.000024	6.17	0.000002*	1.01

To explore the local spatial variation in the relationships between cyclone recovery and the explanatory variables utilised in the global model, the GWR and MGWR models were fitted. These local models can compensate to some extent for the local missing elements in the global regression model and provide deep local perspectives when analysing the spatially varying relationships.

The model diagnostics of GWR reveal an increased adjusted R^2 and reduced AICc. The optimal bandwidth size was found to be 849 neighbours for the coastline, civil defense and cyclone track variables while it was 183 for elevation. Thus, the R^2 value of the model increased to 0.42 while the AICc value decreased to 2091 which is significantly smaller than that of the OLS (2305), indicating a better fit. Amongst all fitted models, the MGWR achieved the highest adjusted R^2 value (0.506) and lowest AICc value (1971).

Figure 8 depicts the spatial distribution of the GWR and MGWR coefficients for the statistically significant regressors. The parameter estimates of the coastline covariate vary across the neighbourhoods (Figure 8 a&b). In the GWR, the coastline variable represents the largest values in some neighbourhoods associated with large amounts of cyclone damage, specifically within North Al-Batnah governorate. In the MGWR, positive values of the coastline coefficients were found across all coastal neighbourhoods of east Muscat, South Al-Batnah, and North Al-Batnah (Figure 8b). These places were characterized by large NTL decreases and low recovery. In both the GWR and MGWR, the number of civil defense centres in each subnational zone was an influential predictor in explaining the spatial variation of damage reduction and cyclone recovery, particularly across the east of Muscat governorate (e.g., Al-Seeb) and north Al-Batnah (e.g., Al-Khabourah) (Figure 8 c&d).

Figure 8 coefficient estimates of local models (GWR & MGWR) representing the effects of the explanatory variables on cyclone recovery. The bandwidth values indicate the number of nearest neighbours.

The GWR coefficients (Figure 8 e&f) take a range of positive and negative values across the study area. The positive GWR coefficients are located in North Al-Batnah governorate (e.g., Al-Khabourah, Sahm, and Sohar). In contrast, the negative GWR coefficients are found within Muscat governorate and in the far east around Sur city. The MGWR coefficient estimates are positive and located mostly in the neighbourhoods of South Al-Batnah and Muscat governorate. The distance to the cyclone track was a significant predictor in describing the spatial variation of NTL-based recovery in the study area (Figure 8 g&h). The GWR parameter estimates vary across the study area, with the largest positive values in some neighbourhoods of east Muscat associated with a large reduction and disturbance of NTL and, thus, low levels of recovery. The negative GWR estimates for elevations are found mainly within the central and northern parts of the study area, suggesting a small correlation between recovery levels and distances to cyclone tracks in these areas. These areas include parts of South Al-Batnah and the entire neighbourhoods of North Al-Batnah. A similar geographical pattern arises in the map of MGWR coefficients, where the variation in coefficients across the study area is depicted. The larger coefficients are found in the northern neighbourhoods, predominantly Al-Khabourah Wilayat indicating a dependence of cyclone recovery on cyclone track. This pattern shows that the proximity to the cyclone track covariate explains the rapid recovery levels where neighbourhoods located near the cyclone eyewall are associated with low recovery. Although approximately all neighbourhoods located near the track of the Shaheen cyclone show consistently small and negative statistically significant coefficients, the impacts of distance to cyclone track in both models (GWR and MGWR) varies significantly spatially. The relationship between y-hat of MGWR and coefficient estimates of cyclone track and elevation (Figure 9a) indicates that larger projected NTL values are associated with large coefficients. Correspondingly, low predicted values (MGWR y-hat) are also associated with low coefficient of determination of coastline civil defence (Figure 9b).

Figure 9 The associations between the MGWR coefficient estimates and predicated NTL values; cyclone track and elevation (a), civil defence and coastline.

Figure 10 illustrates the distribution of spatial heterogeneity concerning model fitting at the subnational level through variations in the local R^2 of the GWR and MGWR. The local R^2 values of the GWR model were large in the central parts of the study area, particularly the neighbourhoods of South Al-Batnah and the coastal neighbourhoods of

North Al-Batnah (Figure 10 a). On the contrary, the local R^2 values were consistently small in the eastern parts (e.g., Muscat governorates specifically Al-Seeb, Bowsher, and Qurayyat) and in the west (e.g., Liwa and Shinas). The R^2 map for the MGWR generally reveals a good fit of the model, with most values being over 0.5 across the region. Indeed, large values were found also across the North and South Al-Batnah governorates (Figure 10 b). Notably, the larger values of local R^2 were associated with neighbourhoods characterized by large destruction and high levels of cyclone damage, whereas the smaller coefficients of local R^2 (R^2<0.5) of Muscat (e.g., east parts) and Al-Sharkya governorates reveal a poorer model fit. This can probably be attributed to the low damage and, thus, high level of rapid recovery and return to normal life. These patterns of local R^2 for the GWR and MGWR models suggest that local models fit better in some areas than others. Therefore, the relationship between the explanatory variables and cyclone recovery is not constant over the study area. It is often the case, however, that relationships between recovery rate and independent variables vary geographically, and the topographical, spatial and physical covariates that support a high level of recovery in one area may not necessarily be the same within another area. This could be for several reasons including spatial variability and the structure of influential factors such as distance to cyclone eyewall, resilience, and other physical conditions.

Figure 10 Coefficient of determination of GWR and MGWR models for recovery rates associated with significant regressors across the impacted neighbourhoods

Table 3 provides the local coefficients of GWR and MGWR, including descriptive statistics (mean, median, standard deviation and maximum). Overall, the OLS model produced more generic patterns that hindered local spatial variation, while the two local models (GWR and MGWR) produced accurate estimates of cyclone recovery rates considering spatial non-stationary, structure and heterogeneity.

Table 3 Summary statistics for the GWR and MGWR parameter estimates.

	GWR					MGWR				
Covariate	**Mean**	**STD**	**Min**	**Median**	**Max**	**Mean**	**STD**	**Min**	**Median**	**Max**
Intercept	-0.071	0.312	-0.898	-0.074	0.777	0.073	0.55	-1.599	0.003	1.57
Coastline	-0.119	0.163	-0.158	0.125	0.511	0.032	0.007	0.012	0.035	0.039
Civil Defence	-0.23	0.451	-0.117	0.072	1.693	0.263	0.464	-0.058	0.057	1.51
Elevation	0.232	0.231	-0.457	0.299	0.631	0.101	0.004	0.092	0.103	0.104
Cyclone Track	-0.005	0.074	-0.183	0.009	0.157	0.002	0.005	-0.007	0.003	0.01

A cross-validation procedure was implemented to gauge spatially the required number of administrative neighbourhoods to fit the local model structure. Therefore, selecting the adaptive kernel method, the AICs estimator was used to determine the optimal and adaptive number of neighbouring administrative zones (Brunsdon et al., 1996). The MGWR calibration induced a matrix of multiscale bandwidths (Table 4) which mirrors the spatial scale of each model process. For example, the covariates of distance to coastline (BW:849 neighbours) and distance to civil defence centre (BW:849 neighbours) operated on the same local scale in the model indicating a process that illustrates a higher degree of spatial homogeneity. On the other hand, elevation operated on a low local scale (BW: 183 neighbours) indicating a locally heterogeneous relationship with cyclone recovery.

The spatial distribution of residuals over the study area can be a vital indicator of model fit and structure. Figure 11 demonstrates the residuals of the global and local models. Overall, the residual values of the three models, which specify how well the model fits the data, are consistently small across all neighbourhoods of the northern and central parts. The local models perform slightly less well in some neighbourhoods of Muscat governorate and Sur Wilayat in the east, represented by large values (red colour) (Figure 11 d&f). Nonetheless, the residual values of the MGWR are generally mid-range and fall around zero, suggesting that the predicted values match closely to the observed values of cyclone recovery, confirming the predictive power of the MGWR model. In the same way, Figure 11 a, c & e plots the fitted residuals against the estimated values of the dependent variables in the global and local models. Although the ranges of the predicted global and local response variables were different, the spatial distribution reveals a random pattern of over-and-under estimation which designates properly specified local models.

Table 4 Multiscale bandwidth for the local MGWR model

Covariate	MGWR Bandwidth	ENP_j	Adj t-val (95%)	Do D_j
Intercept	44	46.777	3.283	0.430
Coastline	849	1.223	2.048	0.970
Civil Defence	849	1.056	1.986	0.992
Elevation	183	9.659	2.803	0.664
Cyclone Track	849	1.282	2.067	0.963

Figure 11 Spatial distribution of residuals: (b) global model, (d) GWR, (f) MGWR. The patterns of fitted model residuals against predicted cyclone recovery: (a) global model, (c) GWR, (e) MGWR.

4. Discussion

The aim of this research was to assess spatially the levels of post-cyclone recovery at different scales after the Shaheen cyclone which hit the northern coasts of Oman in October 2021. We developed an approach to quantify and model the rapid recovery process utilising NTL data and several spatial and topographical predictors. The global regression analysis highlighted some association between NTL-based cyclone recovery and the physical and topographical explanatory variables. However, the local models highlighted the spatial variation in the relationships. Hence, methodologically this research reveals how integrating remote sensing with advanced GIS techniques can be employed to assess cyclone damage and recovery as well as to quantify the spatial variation in recovery rates across settlements over various geographic scales. The outputs of the NTL analysis provide a more pronounced picture of cyclone damage and recovery while both local models (GWR and MGWR) overcome the limitations of global modeling over the northern coastal neighbourhoods of Oman. Moreover, adopting the MGWR, which provided the best fit, in modelling cyclone recovery allowed the relationship between the response and the explanatory variables to vary over the effected neighbourhoods and thus the modelling process operated in different spatial scales. This potential advantage reduced bias in the parameter estimates and thus minimized the under and overfitting errors of model performance.

Spatial modelling of cyclone recovery and resilience at finer spatial resolutions and at multiple scales is still rare. Accordingly, clear knowledge gaps were found, particularly in terms of understanding the spatial and environmental covariates associated with the rate of recovery post-cyclone occurrence. In addition, most existing research lacks any geospatial modelling framework. While most research on cyclone recovery assessment was undertaken from qualitative perspectives (e.g., Pfefferbaum et al., 2013; Uddin et al., 2020; Islam et al.,2017) or focused on non-spatial assessment (N. Lam et al., 2016; Moatty et al, 2021; Islam & Walkerden, 2014), there is a growing literature applying spatial analysis and image processing to quantify geographical patterns (Jaman et al., 2021; Cortés-Ramos et al., 2020; Ahammed & Pandey, 2021), particularly along the cyclone prone-coasts of developing nations. Nevertheless, advanced spatial modeling and simulation of cyclone recovery at subnational levels, especially in developing countries, has not been achieved yet. Indeed, cyclone recovery assessment and, more specifically, geographic variation in recovery patterns, is largely under-researched.

In most developing countries that are susceptible to cyclones, modelling and simulating post disaster recovery is challenging. Indeed, there are substantial barriers to effective post-cyclone recovery particularly availability of datasets, lack of local agencies and recovery managers, lack of national emergency and recovery systems, insufficient computer powers and capabilities. Communities susceptible to destructive natural disasters such as cyclones take months and even years to restore their normal environmental and socioeconomic systems (e.g., rise in water and soil salinity, destruction of major roads, dams, and coastal ecosystems). Thus, post-cyclone spatial assessment of rapid recovery is potentially useful for identifying the most important factors that affect rates of recovery in various contexts. However, little research has been conducted regarding how spatial and environmental determinants of recovery levels vary geographically across the cyclone-prone areas and neighbourhoods.

In this research, the spatial variation in cyclone recovery levels was influenced by a set of topographical and climatic variables including elevation, cyclone track and distance to civil centres. The results indicated considerable spatial heterogeneity in the preliminary cyclone damage and recoveries across the impacted neighbourhoods. Rapid recovery was found mainly within Muscat governorate and towards to the east as well as in the far north, particularly across Liwa, Saham and Sohar. This pattern of rapid recovery was associated with well-established facilities for cyclone preparedness and recovery such as public infrastructure for relief provision and risk reduction. On the other hand, slow recovery was found across the neighbourhoods of the central part of Al-Batnah coastal plain, located within the most affected Wilayats (Al-Musanaah, ASuwayq and Al-Khabourah). In these places, the cyclone eyewall passed near to residential communities and led to severe socioeconomic and environmental disruption including uprooted, broken and twisted date palm trees, and destroyed farms fences and old facilities. Likewise, and along the neighbourhoods of Al-Batnah coastal plain, particularly the central part, many kilometres of several roads were eroded and many farms with agricultural crops were destroyed. Nevertheless, the importance of coastal belts of date palm trees, as a natural barrier to reduce wind velocities protecting buildings and settlements, was evidenced.

The outcome of local models pointed to the substantial influence of proximity to civil defence centres for short-term recovery. The coefficient estimate of this variable was negative (-0.02) specifically in ASuwayq. Neighbourhoods within Muscat in the east and Saham, Sohar, Liwa within North Al-Batnah governorate located in the northern part of the study area produced large coefficient estimates (0.09 to 1.51) compared to other neighbourhoods in the central parts. This distribution pattern seems reasonable as most neighbourhoods in the central part of the coastal plain witnessed larger disturbances and significant damage while most of the neighbourhoods in the east and northern parts had large values of NTL and, thus, faster recovery.

Recovery levels were significantly associated with elevation, specifically in the interior neighbourhoods and settlements located away from the coastline, with a low local association between terrain and recovery in eastern areas (GWR) and northern neighbourhoods (MGWR). The geographical difference in elevation and topography was considered an important indicator for explaining variation in cyclone recovery across the coastal neighbourhoods. Ultimately, areas with large GWR coefficient estimates for this covariate are characterised by hilly and mountainous lands (e.g, within Muscat governorate). Likewise, large coefficients are associated mainly with significant low recovery across North Al-Batnah governorate, specifically neighbourhoods with substantial damage and losses in the electricity sector due to torrential rainfall and high-speed winds.

Both cyclone damage and recovery are essentially associated with physical factors, predominately weather conditions which are considered as natural components of the cyclone structure itself. Commonly, areas located near to cyclone tracks are severely affected by heavy rains and high-speed winds.

The coefficient estimates for distance to cyclone track indicated that overall, the local models identified where particular neighbourhoods were more damaged and illustrated very low and slow levels of recovery, compared to other places located further away from the cyclone track. The damage resultant from the Shaheen cyclone was predominantly associated with several topographic, physical and spatial factors. However, the topographic and climatic variables were dominant drivers in shaping the destructive impacts across the northern coastal neighbourhoods. For example, although the torrential precipitation flooded both the highlands and lowlands, an overflow of water arose from the interior mountainous hinterland, particularly through dry valleys, towards the low-lying coastal areas and caused severe inundation and devastation. Subsequently, neighbourhoods across these low lying areas were characterized by low recovery and a severe decline in NTL compared to interior neighbourhoods.

In the aftermath of the Shaheen cyclone, the Omani government responded to the impacted neighbourhoods with timely support, aid and assistance to reduce the overall impacts. Indeed, not only the civil defense centres, but also the Omani Armed Forces provided immediate relief, particularly across the coastal neighbourhoods of Al-Batnah plain (ASuwayq and Al-Khabourah). Similarly, and before the day of cyclone landfall, the early warning system served to reduce damage including through the timely evacuation of several households in susceptible coastal areas.

This research has several policy implications. First, the predicted patterns of cyclone recovery within local communities can provide spatial guidelines for local planners and governors to develop a long-term disaster management plan across the most cyclone prone areas. Second, identifying spatially the physical and topographical determinants of cyclone recovery patterns at a fine spatial resolution not only can provide invaluable information about cyclone resilience, but also can accurately guide governmental preparedness and intervention pathways to identify local communities at high risk characterized by slow recovery. Third, although the modelling process revealed that some environmental and spatial factors such as population concentration and vegetation density were not significant in explaining the rate of recovery, there are many avenues for future research to develop and include additional variables in the models. Finally, similar spatial modelling processes utilizing NTL data, as well as advanced local models such as GWR and MGWR, can be employed within the susceptible regions in Oman, and in cyclone-prone areas elsewhere.

The results of this study could be used to inform measures to develop a subnational risk reduction plan to mitigate cyclone risks and increase resilience across vulnerable local communities. Similarly, any cyclone management plan at the subnational scale should be developed to enhance community preparedness and increase the resilience of all susceptible settlements to cyclone risks along the north and northeast coasts of Oman. For example, according to the findings of this research, policy-makers can develop a national strategy for disaster management which includes knowledge of where communities and neighbourhoods with slow recovery are located. Such spatial pathways can effectively strengthen institutional early warning systems across vulnerable coastal places. Furthermore, strengthen the recovery activities by increasing the number of civil defense facilities and emergency agencies across the exposed coastal zones specifically across Muscat and Al-Batnah neighbourhoods should lie at the centre of any recovery and preparedness plans.

Most studies in cyclone recovery (e.g., Horney et al.,2017; Brown et al.,2008; Abramson et al.,2010; Miles et al., 2019) have been conducted based on non-spatial frameworks and thus lack the advantages of including spatial driving forces as influential factors in predicting post-disaster recovery. Therefore, comparing with the implemented methods in other studies, our research adopts RS-NTL approach and spatial-based machine learning which offers a proper spatial proxy to measure community's capacity and disaster resilience. Indeed, incorporating NTL and MGWR model has the advantages of capturing spatiotemporal variations of the rapid recovery and provide deeper insights upon geographical recovery patterns.

Furthermore, most existing research into national cyclone recovery evaluations have used qualitative techniques applied to evaluate national-level conditions due to the comparative unavailability of suitable spatial datasets. However, the availability of data in the current study was also impeded by atmospheric conditions, not least the presence of cloud cover. For example, it was impossible to secure an image for 3 October 2021, which was the first day of the Shaheen cyclone. Aggregating the NTL values to small zones rendered the research as an ecological study shaped by the scaling and zoning configuration inherent in the data, known as the Modifiable Areal Unit Problem (MAUP) (Openshaw, 1984; Fotheringham & Wong, 1991). This ecological issue is linked to the unavailability of in-depth information about data pertaining to the destruction and loss impacting ordinary households. Thus, such data were not included in the model fitting. Nevertheless, in addition to reducing the aggregation issue, local models can address the single bandwidth assumption and facilitate the estimation of various optimal bandwidths.

There are various types of recovery measures which have not been included in our analysis particularly those that are not associated directly with electricity and nighttime lights functions in the agricultural and environmental sectors. Nevertheless, and overall, the agriculture pattern in Oman, similar to other desert countries, is a subsistence and domestic farming and it is not a commercial type of agriculture. Households often own small size land and grow some crops particularly date palm trees. Furthermore, the agricultural lands are allocated across administrative zones where settlements, built-up areas as well as agricultural fields are found in the same villages and areas. Consequently, and across the study area there is no any zone which involves only agricultural land but each area includes buildings, facilities, houses and thus electricity. Another potential limitation is that our modelling of cyclone recovery does not quantify other types of damages that were felt by populations and residents of coastal areas after the cyclone. Therefore, it was not possible to measure the recovery levels in crops harvest, and livestock, as well as fisheries. Similarly, it was difficult to assess the recovery rates of other sectors notably damage to fences, wood roofs, gardens, house yards, windows, doors, livestock, road networks, dams and embankments. Nonetheless, and as the electricity is a major daily life service, the assessment of rapid cyclone recovery through NTL provides an effective and reliable measure for planners and decision making. Such analysis may serve as a guide to classify cyclone affected areas and identify places and settlements that recovered faster and those that were characterized by low rates of recovery.

5. Conclusion

Geospatial modelling of cyclone recovery has largely been under-researched and this is due mostly to a lack of detailed relevant spatial datasets. Additionally, research surrounding cyclone damage and recovery is mainly non-spatial, qualitative and involves mixed methods. Studies that examine spatially the association between post-cyclone recovery and socioeconomic, environmental and topographical factors are still rare. Similarly, little research has been conducted on how the determinants of cyclone recovery vary spatially, and whether proximity to institutional mitigation capacity impacts on the rate of recovery. Thus, this research addresses the need to model post-cyclone recovery patterns spatially utilising geospatial techniques at the local community level. Consequently, future research could be carried out incorporating additional socioeconomic and environmental covariates to strengthen the power of model explanation to the spatial variations of post-cyclone recovery.

To explore the relationships between the post- Shaheen cyclone recovery and several socioeconomic, environmental and topographical covariates in Oman, global (OLS) and local (GWR, MGWR) models were fitted and compared. The global model was unable to characterizes adequately the observed spatial variation, while the local models of the relationship between the Shaheen cyclone recovery and four topographical and socioeconomic characteristics of neighbourhoods fitted well. The associations were, thus, found to vary geographically. Further, the MGWR model, which provided the best model fit, explained over 50% of the spatial pattern in cyclone recovery. The findings of this research could serve as effective spatial guidelines for developing cyclone preparedness plans at the local community scale. Furthermore, by identifying the spatial patterns of post-cyclone recovery, this analysis may be of benefit for decision-makers, governors and planners to enhance emergency response systems and reduce the risks associated with tropical cyclones.

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