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Illuminated border: Spatiotemporal analysis of COVID-19 pressure in the Sino-Burma border from the perspective of nighttime light

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ABSTRACT

The emergence of mutant strains such as Omicron has increased the uncertainty of COVID-19, and all countries have taken strict measures to prevent the spread of the disease. The spread of the disease between countries is of particular concern. However, most COVID-19 research focuses mainly on the country or community, and there is less research on the border areas between two countries. In this study, we analyzed changes in the total nighttime light intensity (TNLI) and total nighttime lit area (TNLA) along the Sino-Burma border and used the data to construct an epidemic pressure input index (PII) model in reference to the Shen potential model. The results show that, as the epidemic became more severe, TNLI on both sides of the border at the Ruili border port increased, while that in areas far from the port decreased. At the same time, increases and decreases in TNLA occurred in areas far from the port, and PII can indicate the areas where imported cases are likely to occur. Along the Sino-Burma border, the PII model showed low PII in the north and south and high PII in the central region. The areas between Dehong and Lincang, especially the Ruili, Wanding, Nansan, and Qingshuihe border ports, had high PII. The results of this study offer a reference for public health officials and decision makers when determining resource allocation and the implementation of stricter quarantine rules. With updated epidemic statistics, PII can be recalculated to support timely monitoring of COVID-19 in border areas.

1. Introduction

At the end of 2019, the Coronavirus disease 2019 (COVID-19) was first discovered in Wuhan, China, and causing a global pandemic in early 2020 (Li et al., 2020; Shao et al., 2021). COVID-19 has undoubtedly had a major impact on people, endangering human health in addition to causing widespread social and economic losses (Liu, 2020). All countries have implemented a series of timely measures to prevent and control the epidemic, with Wuhan being the first to implement home quarantine measures and effectively control population migration and the spread of the epidemic (Jia et al., 2020). However, despite the efforts of all countries to control the epidemic, the number of confirmed cases has not stopped increasing and, considering the ongoing virus mutations (e.g., Delta and Omicron strains), COVID-19 will likely persist for a long time. For many countries, after stabilizing the domestic epidemic situation, it is necessary to strictly prevent infections caused by imports. The first confirmed cases in Myanmar were reported on March 24, 2020 (Mya et al., 2020), and the country implemented a “stay at home” program and other restrictions to enforce social distancing (San Lin et al., 2021). Before August 2020, the number of cases increased slowly.

Abbreviations: PII, pressure input index; POI, point of interest; TNLA, total nighttime lit area; TNLI, total nighttime light intensity; VIIRS, visible infrared imaging radiometer suite.
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However, after August 16, the country witnessed a second epidemic wave, and the cumulative number of confirmed cases increased drastically. Since July 2021, as the Delta variant spread, the severity of the epidemic has increased, and Myanmar experienced a third wave of the disease. In China’s Yunnan province, which borders Myanmar, imported cases from Myanmar are closely related to the outbreak in Myanmar. In February 2021, a military coup occurred in Myanmar, leading to frequent unrest and social instability. The national medical infrastructure was already weak and, coupled with the coup, the government could not control the epidemic. China has provided substantial help, such as sending medical workers, oxygen generators, COVID-19 vaccines, and other supplies. Under such circumstances, many Chinese and Burmese residents living in the Sino- Burma border areas prefer to be in China, which has good medical conditions and stable social security, even through illegal immigration. This has placed considerable epidemic prevention pressure on Yunnan province. Imported cases from the border have become a substantial problem for China in its efforts to control the epidemic.

To assess the epidemic pressure on the Sino-Burma border, we studied the nighttime light variability using daily data from the visible infrared imaging radiometer suite (VIIRS). Satellite remote sensing images are an objective data source widely used in economic development, ecological environment and urban area monitoring, population mapping, quantification of electricity consumption, and light pollution assessment (Cai et al., 2017; Havrlant et al., 2021; Lin and Shi, 2020; Wang et al., 2020; Yu et al., 2017; Zhao et al., 2021a).

Many scholars have studied the application of nighttime light remote sensing in epidemic situations. Nightly day/night band (DNB) and monthly composites can monitor the decline and recovery in economic activity levels during the epidemic (Elvidge et al., 2020; Ghosh et al., 2020). Beyer et al. (2021) examined the economic impact of COVID-19 in India through daily electricity consumption and nighttime light intensity. They found that, during the national lockdown, higher COVID-19 infection rates at the district level were associated with greater decreases in nighttime light intensity. Straka et al. (2020) used DNB and NO2 measurement data along with cell phone mobility data and studied the economic and environmental impacts of lockdowns in several cities in America. The preliminary analysis revealed that the reduction in mobility improved air quality and notably reduced economic activity, which indirectly affected the gross domestic product, poverty levels, and unemployment rate. Alahmadi et al., 2021 focused on applying daily nighttime light data to measure the spatiotemporal impact of the COVID-19 pandemic on the human lifestyle in Saudi Arabia at different spatial scales. Xu et al. (2021) used nighttime light data to show that the lockdown of cities against the COVID-19 epidemic directly decreased urban socioeconomic activities.

As most COVID-19 research has focused on individual countries or communities; there is less research on the border areas between countries. The objective of this study was to monitor the epidemic prevention and control situation in border areas using easily available nighttime light remote sensing data and the pressure input index (PII) model to reduce epidemic pressure in Myanmar. We suggest that this method may help to rapidly achieve sustainable development goals affected by the epidemic. In this study, we first calculated and compared the total nighttime light intensity (TNLI) and the total nighttime light area (TNLA) during three periods along the Sino-Burma border. Second, for a more detailed analysis, we created a 5 km buffer area around the border and calculated the TNLI and TNLA in the buffer area during the three periods. Third, we examined severe epidemic occurrences in the border areas. The Shen potential model was improved, and the border epidemic PII was constructed using VIIRS data, normalized difference vegetation index (NDVI) data, digital elevation model (DEM) data, toponym data, point of interest (POI) data, and COVID-19 epidemic statistical data. The PII constructed in this study can make short-term predictions of the epidemic situation in the border area. Through this quantitative and positioning method, we identified border areas that needed to strengthen epidemic prevention and control; moreover, our data provide insights into where illegal immigration incidents are more likely to occur. The results of this study provide a reference for other countries with epidemic-induced border pressures.

2. Data and preprocessing

2.1. Study area

Our study area covered the Sino-Burma border, including Yunnan province in China and Kachin and Shan state in Myanmar (Fig. 1). This area includes three autonomous prefectures (Nuluiang of the Lisu Autonomous Prefecture, Dehong Dai and Jingpo Autonomous Prefecture, Xishuangbanna of the Dai Autonomous Prefecture) and three cities (Baoshan City, Lincang City, Pu’er City) in China and nine districts (Putao, Myitkyina, Bhamo, Muse, Laukung, Kunlong, Lasho, Kengtung, and Mongpha) in Myanmar. The Sino-Burma border is approximately 2,185 km long, with 10 border ports (Houqiao, Nabang, Zhafeng, Ruili, Wanding, Nansan, Qingshiuie, Yonghe, Menglian, and Daluo).

2.2. Data source

Five data types were used in this study: (1) VIIRS daily data, (2) NDVI data, (3) DEM data, (4) POI and toponym data, and (5) epidemic statistical data.

According to the epidemic statistical data, Ruili is the city with the most imported cases in Yunnan province. Ruili is located in Yunnan province (China), opposite the city of Muse in the Shan State of Myanmar. The two cities are closely connected and are key points for border trade (Su and Li, 2021). Lockdowns have been implemented three times in Ruili owing to COVID-19. Data were collected from September 14 to September 21, 2020, March 30 to April 26, 2021, and July 5 to July 25, 2021. The three Ruili lockdown times were closely related to epidemic outbreaks in Myanmar.

VIIRS nighttime light data were obtained from the Earth Observation Group, National Geophysical Data Center, at the National Oceanic and Atmospheric Administration (NOAA: Zhao et al., 2021b). We selected the National Aeronautics and Space Administration (NASA) black marble product suite of the daily moonlight-adjusted nighttime light product (VN462A). This product is processed daily within 3–5 h of acquisition, which means it is sufficiently time-efficient to meet the need for real-time monitoring (Román et al., 2020). The VN462A product is of high quality and has cloud and atmospheric condition corrections (Xu et al., 2021). The resolution of the data is 500 m. After mosaicing, clipping, and projecting the daily nighttime light data during the study period, we used threshold extraction to remove noise. We referred to the methods of Elvidge et al. (2015) and other researchers (Liu et al., 2016; Xu et al., 2021) for the processing of night light data. An artificial light area is stable for a short time, whereas noise is unstable throughout the time-series of images, making the removal of noise possible. We first synthesized daily data into weekly data. Then, compared with the ESRI World Topo Map, the Digital Number (DN) value on the boundary of the light gathering area was selected as the threshold for processing. Through continuous testing, the noise was removed until the processed image retained a stable light source to the greatest extent; 7.5 was used as the final threshold.

The VIIRS daily data were from 1 week before and 1 week after each lockdown. We collected 21 days of VN462A data during the first lockdown and then composited them for 3 weeks; the second lockdown data were for 42 days, and the data were synthesized for 6 weeks; the third lockdown data were synthesized for 5 weeks (Table 1).

| Data Type | Description | Resolution | Acquisition Period |
|-----------|-------------|------------|--------------------|
| NDVI      | Normalized difference vegetation index | 500 m       | 2021              |
| DEM       | Digital elevation model | 500 m       | 2021              |
| POI       | Point of interest data | 500 m       | 2021              |
| Toponym   | Toponym data | 500 m       | 2021              |
| Epidemic  | Statistical data | 500 m       | 2021              |
morphological parameters such as slope, aspect, and curvature can be extracted (Zhou and Liu, 2004). We collected Shuttle Radar Topography Mission (SRTM) DEM data from NASA (https://dwtkns.com/srtm30m/), which has a resolution of 30 m. As the difficulty of crossing between two border areas is closely related to the terrain, we performed a slope analysis on the DEM data and extracted the slope and elevation of the study area. To facilitate matching with the VIIRS data, we resampled the NDVI and DEM data to 500 m using the bilinear interpolation method.

POI and toponym data have similar attributes. Both contain exact location information (i.e., latitude and longitude) and additional details such as names and categories (McKenzie et al., 2015). However, POI data contain more urban information, while toponym data contain more rural information (Zhao et al., 2020). We searched for POI and toponym data from BigeMap (https://www.bigeemap.com/) and the Chinese National Database of Geographical Names (https://dmfw.mca.gov.cn/online/map.html). Then, we filtered the POI and toponym data, deleted duplicate data, and obtained the PT (POI & toponym data) dataset. This study performed kernel density estimation using the PT dataset to calculate aggregation and spatial distribution of POI and toponym data; the results provided population aggregation. After continuous testing, we performed kernel density estimation on the PT dataset with a bandwidth of 5,000 m and an output radius of 500 m.

We collected data on the COVID-19 epidemic in Yunnan Province of China (https://ynswsjkw.yn.gov.cn/web/index) and Myanmar (https://www.mohs.gov.mm/) starting from the day the first confirmed case was reported on August 1, 2021. After organizing the data, the epidemic data of Myanmar during the second lockdown could not be searched. Therefore, the data used in this study are confirmed case data for the first and third lockdowns.

3. Methods

To analyze the COVID-19 situation on the Sino-Burma border from the perspective of nighttime light, we used the following methodology. From a macroscopic viewpoint, we first calculated the numerical changes in TNLI and TNLA in the study area. Subsequently, we created a buffer zone within 5 km of the boundary to calculate the numerical changes in TNLI and TNLA in the buffer area. From a microscopic viewpoint, we analyzed the TNLI and TNLA of the Ruili port in time and space. Finally, based on the concept of the Shen potential model, we constructed the PII to measure the input pressure of COVID-19 on the Sino-Burma border. The following flowchart shows the main methods employed in this study (Fig. 2).

3.1. Analysis of changes in TNLI and TNLA

The most direct quantitative evaluation method is estimation of the amount of nighttime light for each region. Therefore, we calculated the TNLI in China, Myanmar, and the entire study area every week and then converted the calculated TNLI data into a statistical chart. TNLI only calculates the total brightness value, but COVID-19 may also affect...
changes in the area of nighttime light. For example, areas that did not have light initially may have had light owing to epidemic prevention and control measures. For example, China has built approximately 500 km of protective fence along the border, which is equipped with searchlights to prevent people from illegally crossing the border from Myanmar. Therefore, we calculated TNLA, which can show changes in the lit area every week.

As China’s imported cases are mainly reported from land ports on the border, we focused on the border area. We compared several ports on the border and measured the light range. After many tests, we finally selected a buffer distance of 5 km, which can most completely calculate the light intensity on the border. We also calculated the TNLI and TNLA of the border buffer area and analyzed their changes. Note that TNLI is calculated based on the DN value of all pixels in a region, and TNLA is the statistics of the number of grid changes, they have no physical units.

3.2. Spatiotemporal analysis

The calculation of TNLI and TNLA can only provide changes in numerical values but cannot discern changes in spatial details. To further study the spatial changes of nighttime light, we performed ArcGIS raster calculation and reclassification to spatialize the results and observe the spatial variation in intensity and area.

Using the raster calculator in ArcGIS, we could directly calculate the change in nighttime light intensity. The raster calculator is a spatial analysis function tool that can input map algebra expressions and use operators and functions to perform mathematical calculations. The calculation equation of light intensity and lit area change is as follows:

\[
\text{change} = \text{week}_c - \text{week}_f
\]  

(1)

We chose the week with the largest change in intensity and area during the lockdown period and recorded it as week_c. We then compared week_c with the first week, recorded as week_f. The result greater than 0 indicated increased intensity, −0 indicated no change in intensity, and less than 0 indicated decreased intensity.

The change in lit area from VIIRS data was classified using the reclassification tool in ArcGIS and then calculated using the raster calculator. The reclassification tool can reclassify the input pixel value or change the input pixel value to an alternative value. In the reclassification of week_c and week_f lit area, areas with a brightness value were assigned as 1, and those without a value were assigned as 0. We then calculated the reclassified data using equation (1) in the raster calculator. A calculation result of −1 indicated a decrease in the lit area, 0 indicated no change, and 1 indicated an increase in the lit area.

3.3. PII construction

To quantify the pressure of border prevention and control, we constructed the PII model by referring to the Shen potential model, which is a typical model for measuring the accessibility index (Shen, 1998). The model evaluates the difficulty of obtaining certain reachable services or resources from the perspective of spatial interaction and was improved by Shen after considering the “demand side” based on the Hansen potential energy model (Hansen, 1959). To calculate the accessibility of a point (supplier), we need to consider not only the potential of the point but also the potential from that point to another point (demand). Only when the supply and demand factors are considered in the accessibility calculation can we comprehensively investigate accessibility in each district. This can be understood as the spatial interaction between the epidemic output and input areas. The formula is as follows:

\[
P_{ij} = \sum_{i=1}^{N} P_i f(C_i) \frac{1}{d_{ij}}
\]  

(2)

where PII is the epidemic pressure input index, P_i is the number of confirmed COVID-19 cases in area i, d_{ij} is the weighted distance from area i to grid j, f(C_i) is the spatial barrier function from area i to j, and i is the district of the Myanmar border area. Except for statistical data, all data were processed into 500 m grid data. We used five factors to calculate f(C_i), namely, NDVI, elevation, slope, toponym and POI density, and nighttime light intensity. These five factors were standardized before calculation, which was performed as follows:

\[
f(C_i) = \sqrt{N \times \left( \frac{1}{E \times S} \right) \times \log(PT + NL + 1)}
\]  

(3)

where N is NDVI and the higher the NDVI, the denser the vegetation, which is more conducive to covert border crossing. E is elevation, and S is slope. The lower the elevation and the gentler the slope, the easier it is to enter area j. When the values of E or S are equal to zero, a 3 × 3 or 5 × 5 neighborhood range can be used to calculate the mean value as a new value. The basic idea of neighborhood analysis is to take the grid pixel with a value of zero as the center, expand the certain range to the

![Fig. 2. Methodological flow chart. Visible infrared imaging radiometer suite (VIIRS); normalized difference vegetation index (NDVI); digital elevation model (DEM); point of interest (POI); total nighttime light intensity (TNLI); total nighttime lit area (TNLA); pressure input index (PII).](image-url)

| Data                        | Preprocessing                      | Methods                      |
|-----------------------------|------------------------------------|------------------------------|
| VIIRS                       | Preprocessing                      | Calculate TNLI and TNLA in   |
| NDVI                        | Composed weekly data               | study area                   |
| DEM                         | Resample                           | Calculate TNLI and TNLA in   |
| POI                         | Slope analysis                     | buffer area                  |
| Toponym                     | Filter and delete                  | Spatiotemporal analysis     |
| Epidemic statistical data   | Organize data                      | Construct PII                |

| Operators and functions to perform mathematical calculations. The raster calculator is a spatial analysis function tool that can input map algebra expressions and use operators and functions to perform mathematical calculations.
surrounding area, and then perform a function operation based on the value of the extended pixel to obtain a new value. \( PT \) was obtained from the kernel density estimation of POI and toponym data, and \( NL \) is the nighttime light intensity of grid \( j \). \( PT \) and \( NL \) can reflect the degree of population aggregation and economic development in area \( j \) to a certain extent. Larger values represent greater attraction for people to migrate. To seek better treatment, people in the epidemic output area will prefer to go to areas with large populations and robust medical facilities. As \( PT \) and \( NL \) may have a value of 0 in the border area, adding 1 ensures that the independent variable is greater than 1. The larger the value of \( f(C_{ij}) \), the smaller the spatial barrier, and the easier it is for the population to flow between the two adjacent border areas.

4. Results

4.1. Changes in TNLI and TNLA of the whole study area

As shown in Fig. 3 (a), although TNLI fluctuated during the second lockdown, the light intensity of the entire study area decreased during the first and third lockdowns. This was due to a reduction in human activity during the lockdown period (Xu et al., 2021; Yin et al., 2021). The light intensity change curves of China and Myanmar showed consistent trends with those of the brightness change throughout the study area.

However, the trend of TNLA differed from that of TNLI. As shown in Fig. 3(b), although the intensity decreased, the lit area increased during lockdowns. This may be because large shopping malls, factories, and office buildings were closed and more people stayed in residential areas.

4.2. TNLI and TNLA variations in the border buffer area

As shown in Fig. 4(a), before and after the first lockdown, the light intensity of the border area decreased significantly. As a consequence of COVID-19, ports were closed, trade between China and Myanmar stopped, and human activity decreased. During the second lockdown, the light intensity of China’s border area increased and then decreased twice, whereas the brightness value in Myanmar’s border area increased. According to news reports, Ruili, in the border buffer area, conducted emergency nucleic acid detection for all citizens at night in the second week, resulting in an increase in TNLI in the second week. In the third lockdown period, TNLI first decreased, then increased, and then decreased again.

Fig. 3. Changes in total nighttime light intensity (TNLI) (a) and total nighttime lit area (TNLA) (b) in the study area during the three lockdowns.
Fig. 4 (b) shows the changes in the TNLA in the border buffer area during the three lockdowns. The first lockdown measure was only implemented for one week, and the lit area increased significantly (from week1 to week2). The second and third lockdowns lasted longer, and the lit area of the border buffer area increased and then decreased. The increase in lit areas was not only due to lighting in residential areas but also due to epidemic prevention and control measures in border areas. After the lockdown, the lit areas expanded to the boundary, and night patrols were strengthened. When COVID-19 was controlled, the lit area gradually decreased.

When comparing the results of the study area and the border buffer area, there were significant differences in light intensity and lit area between China and Myanmar throughout the study area. However, in the border buffer area, the gap between the light intensity and the lit area of the two countries narrowed. This shows that during the epidemic period, both countries were very concerned about border epidemic management.

### 4.3. Spatiotemporal changes in nighttime light

Fig. 5 shows the results of the spatiotemporal analysis of light intensity and lit area after three lockdowns. We selected Ruili port on the Sino-Burma border for detailed analysis. In Fig. 5, bright green indicates a decrease in lit area, bright red indicates an increase in lit area, light green indicates a decrease in light intensity, and light red indicates an increase in intensity.

During the first lockdown period, the light intensity on both sides of the border decreased significantly, and both the light intensity and the lit area increased away from the border port area. This may have been due to the Chinese government’s measures to close the Sino-Burma border, resulting in decreased light intensity. The light change of the second lockdown differed greatly from that of the first. During the second lockdown period, the light intensity on both sides of the border increased significantly, while the lit area in Muse (Myanmar) increased. As the second lockdown was imposed to prevent illegal immigration of patients with COVID-19 from Myanmar, the government implemented strict prevention and control measures in the Sino-Burma border area. Night patrols in border areas were strengthened, resulting in increased light intensity at night. During the third lockdown period, the light intensity in the areas near the border continued to increase. Nevertheless, in contrast to that in the second lockdown, the spatial distribution of the intensity increase area was more dispersed. This period coincided with the third outbreak of the epidemic in Myanmar. Myanmar recorded thousands of confirmed cases every day, of which Muse added dozens
Each day, Muse also implemented “stay at home” measures to reduce personnel mobility.

In the area southwest of Ruili port, although there was no obvious light change during the first lockdown, light change was observed during the second lockdown, and to an even greater extent, during the third lockdown. Prior to the outbreak of COVID-19, there was practically no human activity in this region. As the epidemic situation in Myanmar continued to worsen and the border port was closed, an increasing number of people entered China illegally. To prevent this behavior, China built a fence along the border and placed many personnel on duty on the border. This may explain the light changes in this area.

In summary, our results show that with the outbreak of the epidemic,

![Diagram](image_url)

**Fig. 5.** (a) Changes in light intensity and area during the first lockdown; (b) changes in light intensity and area during the second lockdown; (c) changes in light intensity and area during the third lockdown; and (d) the second weekly visible infrared imaging radiometer suite (VIIRS) images during the second lockdown.

![Diagram](image_url)

**Fig. 6.** Pressure input index (PII) distribution during the first lockdown. The higher the PII value, the greater the likelihood of imported cases in the border areas.
the governments of both countries paid increasing attention to the management of the epidemic on the Sino-Burma border. As the epidemic became more severe, the light intensity on both sides of the border increased, and the light intensity in areas far from the port decreased. However, both increases and decreases in the lit area occurred far from the port.

4.4. PII grading and the pressure of epidemic import

Owing to a lack of detailed data on the second Myanmar epidemic, we calculated the PII during the first and third lockdowns only (Fig. 6 and Fig. 7, respectively). The natural break method was used to divide PII into five levels: lower PII, low PII, medium PII, high PII, and higher PII. Along the Sino-Burma border, the overall epidemic pressure was low during the first and third lockdowns. Together, lower and low PII accounted for 75.35% and 70.46% of the study area, respectively, and PII showed a spatial distribution trend of low values in the north and south and high values in the central area.

(1) Lower PII levels during the first and third lockdown periods accounted for 40.31% and 36.62% of the study area, respectively. Compared with that of the first lockdown period, the border area with a lower PII in the third lockdown decreased. The lower PII area was distributed on the north and south sides of the Sino-Burma border. The terrain in the north is relatively high, and the two countries are separated by high mountains. The terrain in the south is relatively flat, but few people live within 10 km of the southern border.

(2) Low PII levels during the first and third lockdown periods accounted for 35.04% and 33.84% of the study area, respectively. The area with this level was mainly distributed between the medium and lower PII areas. Compared with that in the first lockdown, the distribution range of the low PII level obviously expanded to the north and south in the third lockdown. There were people living around the border in the low PII area, and the movement of people may have led to imported cases.

(3) Medium PII levels during the first and third lockdowns accounted for 15.62% and 20.17% of the study area, respectively, mainly within Daluo, Menglian, Zhangfeng, and some areas of Dehong and Lincang. Compared with the change in all levels in the two periods, the change in the medium PII level was the largest. During the third lockdown, medium PII along the border area from Zhangfeng port to Qingshuihe port increased, and most areas changed from the original low PII to medium PII.

(4) During the first and third lockdowns, high PII accounted for 7.34% and 7.55% of the study area, respectively, mainly distributed around Naban port and higher PII level areas. During the first lockdown, high PII was mainly distributed in the border area west of Ruili port. During the third lockdown period, high PII not only included the western border area of Ruili port but the area east of Ruili port to Wanding. This change reflects the increased border patrols initiated to prevent illegal immigrants from entering China.

(5) Higher PII during the first and third lockdown periods accounted for 1.69% and 1.81% of the study area, respectively, mainly distributed around the Ruili, Wanding, Nansan, and Qingshuihe border ports in Dehong and Lincang. Higher PII values in these areas were caused by three factors. First, there is no natural topographic barrier between Dehong and Myanmar to block the border; cities are connected to cities, villages are connected to villages, and farmland is next to farmland. Illegal immigrants are more inclined to enter China from Dehong than from areas of high terrain and difficult border crossings. Second, there are four ports along the Dehong border and three ports on the Lincang border. When there is no epidemic, these ports play a significant role in the economic and trade relationship between China and Myanmar, and many Chinese businesses operate in Myanmar. When the epidemic situation in Myanmar became serious, Chinese citizens stranded in Myanmar were eager to return home.
and long lines of people formed at border ports. Third, China issued policies to urge illegal personnel in Myanmar to return to their homes immediately; otherwise, China will cancel their registered residence. In summary, the higher PII of the Dehong and Lincang ports reflect government investment in controlling the epidemic situation.

5. Discussion

5.1. Unpopulated borderlands

The kernel density estimation results of the PT dataset show that there was no toponymy or POI distribution in many places along the border. Border areas often suffer from a poor ecological environment, distance from urban centers, and low economic development (Li et al., 2021). As border area populations are often small, we considered whether unpopulated borderlands (i.e., a state of emptiness relative to neighboring countries due to the migration of permanent residents from the border; Bai and Tan, 2017) would appear along with the intensification of the epidemic. The human relative activity index (H) was calculated according to Bai and Tan’s research (2017) as follows:

\[
AL = \frac{TNLI}{S}
\]

\[
H = \frac{AL}{AL_i}
\]

where AL is the average light intensity in the border buffer, TNLI is the total nighttime light intensity in the buffer area, S is the area of the border buffer zone, and i and j represent the two countries in the border buffer zone. If H is greater than 1, human activities in the border area of country i are more active than those in area j. If H is less than 1, human activities in country i are not as intensive as those in area j. We calculated the H index of the Sino-Burma border during the three lockdowns (Fig. 8).

It can be seen that H was greater than 1, indicating that human activities in China were greater than those in Myanmar during the epidemic. However, the H between China and Myanmar fluctuated and continued to decline, and the unpopulated borderland trend grew more obvious over time. Owing to frequent epidemic outbreaks along the border, residents living along the border moved away from the border area, which negatively affected border security and social stability.

5.2. Difficulties in epidemic prevention in border areas

Border areas are important national homeland security barriers and gateways to the outside world (Song et al., 2017). With the COVID-19 pandemic, restricting cross-border population movement between countries is an important measure to reduce the spread of the disease. China’s land border is 22,000 km long, and China is adjacent to many countries. In addition to border ports, border crossings are possible at mountain passes and ferry crossings and from paths along the border, making the border difficult to secure. China has enacted many prevention and control measures along the border; police, militia, and villagers have been mobilized 24 h border patrols, wire fences have been installed, and outposts have been established every 500 m. People living in border areas are being vaccinated for COVID-19. In addition, nucleic acid testing is performed once every other day for staff working at border ports, hospitals, and isolation facilities and twice a week for other staff. Strict control of the flow of people in port cities is also underway. People leaving the port city must have a negative nucleic acid test certificate obtained within 48 h prior to their travel. Furthermore, the Chinese government has sent professional medical teams to neighboring countries to help provide masks, protective clothing, vaccines, and other materials. It is believed that with the cooperation of China and neighboring countries, the epidemic will eventually be controlled.

6. Conclusions

This study conducted a quantitative analysis of the COVID-19 epidemic along the Sino-Burma border from the perspective of nighttime light. We compared changes in light intensity and lit area along the border and, in finer detail, for a border port zone. The results show that, as the epidemic became more severe, light intensity on both sides of the border in the port area increased, while light intensity in areas far from the border port decreased. In contrast, both increases and decreases in lit area occurred in areas far from the border port. Using a combination of NDVI, DEM, POI, toponym, and epidemic statistical data, we improved the Shen potential model to construct PII, which was divided into five levels. In the Sino-Burma border area, PII was found to be low in the north and south and high in the central region. The areas between Dehong and Lincang, especially Ruili, Wanding, Nansan, and Qingshuihe, had high PII. Special attention should be paid to these areas to prevent the entry of imported patients with COVID-19. The greatest advantage of the PII model is that because other variables are fixed and only epidemic statistical data are changed, the PII can be recalculated based on updated number of COVID-19 daily confirmed cases. As such, our model offers a tool to monitor and predict the short-term epidemic situation in border areas. Future research will consider the establishment of corresponding buffer zones for areas with different levels of PII, which would help decision makers to reasonably allocate human resources. Although additional research and refinement are required, the approach described here can provide a valuable tool for epidemic monitoring from a new perspective.

CRediT authorship contribution statement

Fei Zhao: Conceptualization, Funding acquisition, Methodology, Writing – original draft. Sujin Zhang: Conceptualization, Funding
acquisition, Methodology, Writing – original draft. Degang Zhang: Software. Zhiyan Peng: Visualization. Hongyun Zeng: Writing – review & editing. Zhifang Zhao: Writing – review & editing. Wei Jin: Software. Wenyu Shen: Data curation. Wei Liu: Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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