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Importance of community containment measures in combating the COVID-19 epidemic: From the perspective of urban planning

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ABSTRACT

To contain the outbreak of COVID-19 in Wuhan, unprecedented interventions, including city lockdown and community closure, have been implemented. However, most of the current studies focused on evaluation of the city lockdown, but paid limited attention to the impacts of the community containment measures within the city. This research addressed this important issue from the perspective of urban planning, based on the epidemic and remote sensing data of 194 communities of Wuhan. We found that the number of confirmed cases of communities is highly related to urban planning factors, e.g. area percentage of buildings and density of neighboring markets. These factors are relevant to the residents' activity patterns, which therefore impact the mode of virus transmission. Our research confirmed the effectiveness of the community-oriented control strategies, provided a valuable reference for other cities that are suffering from the epidemic, and exhibited new thoughts into future urban planning.

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SARS-Cov-2; close-off; transmission; remote sensing; landscape; city layouts; infection disease; healthy city

1. Introduction

Coronavirus disease 2019 (COVID-19) is caused by infection of the severe acute respiratory syndrome coronavirus 2 (SARS-Cov-2). The first case of COVID-19 in Wuhan, the most populous city (over 10 million) in Central China, was reported in late December, 2019. In the following months, this disease spread rapidly in Wuhan and to the neighboring cities due to the high transmission capacity of the virus and the massive human movement before the Chinese Lunar New Year (Wu et al. 2020). A range of prevention and control measures were adopted in Wuhan since the confirmation of human-to-human transmission (Chen et al. 2020b). The most notably, the lockdown was implemented in Wuhan on 23 January, 2020, from when all public transport services were suspended, and people were prohibited to leave Wuhan without official permission. These unprecedented measures prevented large numbers of people from moving in and out of Wuhan, and effectively reduced the dissemination of the virus from Wuhan to other cities, which is of paramount importance for restraining a national outbreak (Kraemer et al. 2020; Lau et al. 2020; Tian et al. 2020). However, in spite of the shutdown of the city, the number of confirmed cases in Wuhan still increased rapidly (Figure 1), owing to the difficulty in diagnosis, insufficiency of protective equipment and medical supplies, and excessive density of urban population (Guan, Chen, and Zhong 2020). In this emergency situation, to curb the spread of this infectious disease among crowds,

Wuhan government further implemented a stringent control management on the basis of communities (so-called close-off management of communities) since 11 February, 2020. This community containment aimed to restrain all residents to stay home, and their daily needs (e.g. food, supplies, and medicines) were offered through on-line shopping and delivered by the community managers and volunteers. After the great efforts and sacrifices, the outbreak in Wuhan has been brought under control, and the lockdown was relived on 8 April 2020. It can be said that the outbreak and control of COVID-19 in Wuhan provides a valuable reference for other cities or countries that are suffering from the epidemic.

The epidemic in Wuhan has drawn worldwide concerns, and researchers have made their utmost efforts to deepen our knowledge of this novel virus from different aspects, including biological properties of the virus (Hackbart, Deng, and Baker 2020; Ou et al. 2020; Yan et al. 2020), clinical characters of infected patients (Chen et al. 2020a; Guan et al. 2020), diagnosis and treatment of the disease (Duan et al. 2020; Luo et al. 2020; Shi et al. 2020), and transmission patterns of this epidemic (Huang and Qiao 2020; Kucharski et al. 2020; Tian et al. 2020; Wells et al. 2020). From the perspective of public health management, throughout the whole process of Wuhan in combating COVID-19, the lockdown of the city and the close-off of communities are two crucial events. However, nearly all the current studies focus on the efficacy of the city lockdown from a macro standpoint

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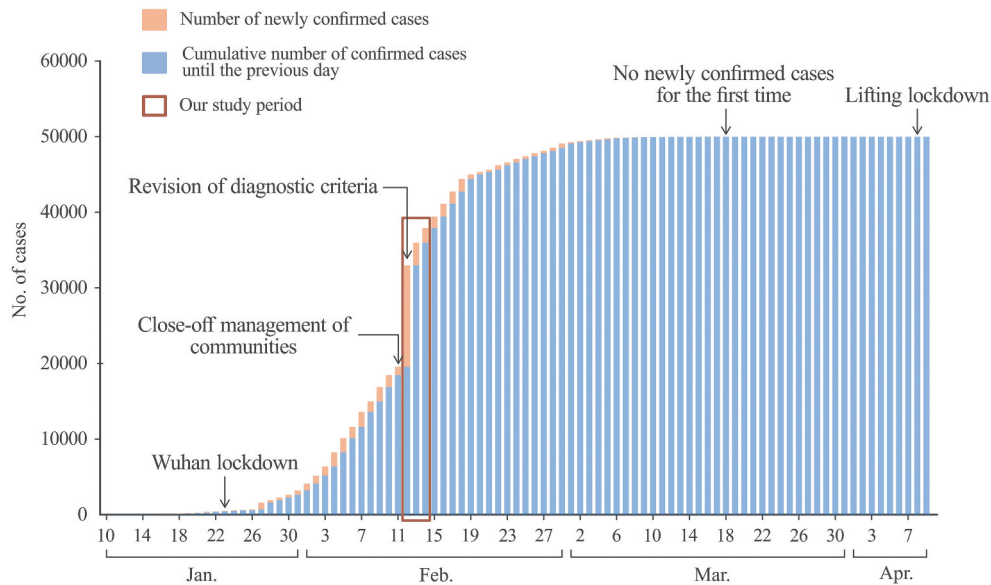


Figure 1. Epidemic curves and key events during the COVID-19 outbreak in Wuhan.

(Chinazzi et al. 2020; Kraemer et al. 2020; Lau et al. 2020; Tian et al. 2020), but ignore the analysis of the community close-off within the city, from a micro point of view. The lockdown effectively blocked the transmission of the virus from Wuhan to other cities (Kraemer et al. 2020; Tian et al. 2020), nevertheless, the micro-scale interventions became the key for controlling the epidemic of Wuhan.

Previous studies have shown that urban planning can influence the pattern of residents' daily activities and local climate, which in turn affects the mode of virus transmission. For example, Li and Zhang (2003) thought that the increase in urban green space could increase air oxygen and ventilation capacity, and would provide more places for residents to exercise, which was benefit for the prevention and control of SARS epidemic in 2003. Murdock et al. (2017) found that urban impervious surfaces were closely related to urban microclimates, which would influence mosquito breeding and thus the spread of the dengue virus. In addition, recent studies also indicated that the urbanization features and urban spatial factors could also influence the COVID-19 pandemic (Connolly, Ali, and Keil 2020; Li et al. 2020; Rastandeh and Jarchow 2020). The close relation between urban landscape and virus transmission provides new insights into the role of community interventions for the COVID-19 epidemic control. For example, before the close-off of communities, residents can move freely, and more infections would appear in communities with higher building density and more public facilities nearby, owing to the relatively higher frequency of human contacts. However, after implementing the strict community containment measures, all residents were required to stay home, and the transmission between humans had been significantly cut off in the communities. Therefore, this

research aims to reveal the importance of the strict community control by investigating the relationship between the number of confirmed cases and urban planning (e.g., percentage and layout of buildings, distributions of public facilities, and other aspects), based on the remote sensing and geographical information data. To our knowledge, no study has evaluated the prevention and control measures of the COVID-19 epidemic from the perspective of remote sensing and urban planning. Meanwhile, the impacts of community-level interventions have not been comprehensively investigated yet.

In this study, the cumulative numbers of confirmed cases (CNCC) in 194 communities of Wuhan (Figure 2) were used to explore the impacts of urban planning on the COVID-19 epidemic. Seven representative metrics (see Methods) were selected to describe the urban planning from various aspects, and all of them were calculated in each community based on high-resolution remote sensing and geographical information data.

2. Data

The cloud-free remote sensing images acquired on October 2018 from the ZiYuan-3 (ZY-3) satellite were used to map the land covers in Wuhan. The ZY-3 satellite is the first high-resolution stereo mapping satellite of China (Li, Wang, and Jiang 2020; Xu, Gong, and Wang 2014), and can provide images with panchromatic (PAN) (2.1-m spatial resolution) and multi-spectral (MS) bands (5.8-m spatial resolution) (Liu et al. 2019). Besides, additional geospatial data, including the three-dimensional building data and road networks, were applied to produce the land cover maps. The three-dimensional building data were provided by the Wuhan Land Resources and Planning Bureau, including footprint and height for

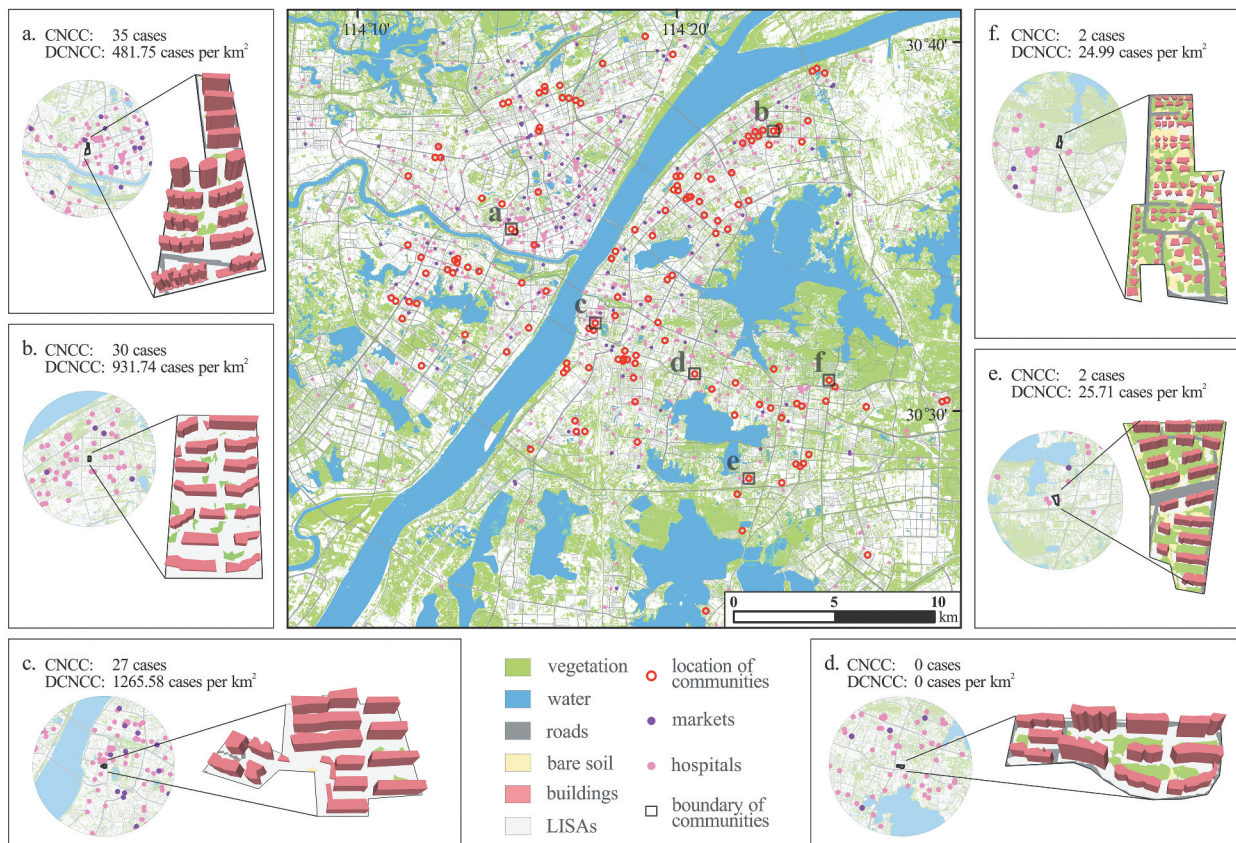


Figure 2. Spatial distributions and land cover maps of the 194 communities in Wuhan. CNCC means the cumulative number of confirmed cases of each community, and DCNCC is the density of CNCC (i.e. the ratio of CNCC to the area of the corresponding community). LISAs means low-layer impervious surface areas (e.g., squares and open areas).

each building. Road networks were collected from the OpenStreetMap (OSM), which is an open data source obtained by large amounts of volunteers collaboratively (<https://www.openstreetmap.org>). In addition, the boundaries of communities, and the locations of hospitals and markets were derived from the AMap, a famous web mapping, navigation, and location-based services provider in China (<https://www.amap.com/>). These geospatial data were carefully examined by visual inspection, and further modified by manual editing if necessary.

The community-level COVID-19 epidemic data, including the name of community, the date of epidemic information, and the cumulative number of confirmed cases (i.e. CNCC) till the date, were made public by the management committee (the local government) of each community. The collection, collation, and dissemination of the epidemic data in each community were under the strict supervision of the management committee. Allowing for the rapid increase of confirmed cases, the report date of epidemic information shall be close enough when using the epidemic data from different communities. In this study, we focused only on the communities where the epidemic data were available from Feb 12, 2020 (the first day after the close-off of communities) to Feb 14, 2020. The data during the three days were selected because of the following

reasons: (1) From February 12, the diagnosis was revised by the Hubei government, i.e., cases were confirmed by clinical diagnosis through radiologic findings, neutrophil counts and epidemiologic links (Yang et al. 2020), which led to the addition of large amounts of previously omitted cases, and (2) more importantly, the CNCC during this period can exactly reflect the epidemic situation before the close-off of communities. In addition, a small time span (three days) was chosen in order to ensure a fair comparison between different communities. In this way, 194 communities were finally included in our analysis. Please also notice that the density of the CNCC (i.e. DCNCC, CNCC divided by the area of the corresponding community) was calculated and adopted for the statistical analysis, in order to exclude the influence of the size of communities to the CNCC.

3. Methods

3.1 Land cover mapping of Wuhan

In this study, ZY-3 images, building footprints and OSM road networks were integrated to map the high-resolution land cover (2.1-m) of Wuhan. The study area was classified into six land-cover categories: buildings, vegetation, bare soil, water, roads, and low-

layer impervious surface areas (i.e. LISAs, e.g., squares and open areas) (Figure 2). Buildings and roads were firstly extracted by referring to the building footprint and road network data. After that, a supervised classification method based on the random forest classifier was applied to identifying the other four land cover categories. From the land cover map, 50 samples for each category were randomly selected for validation, and the overall accuracy was over 90% (Table 1), implying the reliability of the mapping results. Please refer to our previous works (Huang and Wang 2019; Huang et al. 2020) for more details for the land cover mapping.

3.2 Urban planning metrics

A total of seven metrics was included in this study to represent the layouts of communities (Table 2). Buildings in communities are closely related to the residents' daily activities, and hence, three metrics, including area percentage of buildings, distance among buildings, and height of buildings, were selected to describe the density, distribution, and vertical characteristic of buildings in each community, respectively. Communities with larger, taller, and denser buildings tend to accommodate larger populations, and with that comes more opportunities for human contact, which may lead to an increased risk of cross-infection among residents. LISAs is used to represent the public activity spaces (e.g. squares and roads) in communities. The public activity spaces are the major

regions for residents' daily activities (fitness, chitchat, etc.) in communities, and changes in their size may affect the frequency of residents' contact and thus the spread of the epidemic. Besides, the area percentage of vegetation was included in this study, due to its important role in urban environment and residents' health (Salmond et al. 2016; Wang et al. 2019; Lauko et al. 2020). On the other hand, two crowded places around communities, hospitals, and markets, providing medical services and daily necessities, respectively, were also considered in our analysis, by calculating their distance-weighted density around the communities. In particular, the densities of hospitals and markets are of interest since they are the places where the neighboring people have to go, in spite of the city lockdown. In summary, these urban planning metrics are closely related to the daily activities of citizens, and hence, can influence the viral transmission.

3.3 Statistical analysis

In this study, communities were considered as the basic analysis units, and the Mann-Whitney U test (Mann and Whitney 1947) was used to examine if an urban planning metric differed significantly between low- and high-DCNCC communities. The relationship between DCNCC and each urban planning metric was evaluated by the Spearman's rank correlation analysis (Sedgwick 2014), on the basis of the 194 communities in Wuhan. The value of the Spearman's rank correlation analysis ranges from -1 to 1 , and

Table 1. Confusion matrix for the high-resolution land cover map of Wuhan. UA, PA, and OA are user's accuracy, producer's accuracy and overall accuracy of the land cover map, respectively. LISAs means low-layer impervious surface areas (e.g., squares and open areas).

	LISAs	Vegetation	Buildings	Water	Bare soil	Roads	UA (%)
LISAs	45	1	1	2	1	0	90.00
Vegetation	0	47	0	0	3	0	94.00
Buildings	2	0	48	0	0	0	96.00
Water	3	1	1	45	0	0	90.00
Bare Soil	0	0	2	0	48	0	96.00
Roads	0	4	2	0	0	44	88.00
PA (%)	90.00	88.68	88.89	95.74	92.31	100.00	
OA (%)							92.23

Table 2. Urban planning metrics used in this study.

Metric	Formula	Description
Area percentage of buildings	$\frac{a_{building}}{A}$	$a_{building}$ is the total footprint area of all buildings in a community, and A is the area of corresponding community.
Distance among buildings	$\sum_{i=1}^n \frac{dist_{building_i}}{n}$	$dist_{building_i}$ is the distance of the i th building from its nearest building in the community, and n is the number of buildings.
Height of buildings	$\sum_{i=1}^n \frac{h_{building_i}}{n}$	$h_{building_i}$ is the height of the i th building in a community.
Area percentage of LISAs	$\frac{a_{LISAs}}{A}$	a_{LISAs} is the total area of all low-layer impervious surface areas (LISAs) in a community.
Area percentage of vegetation	$\frac{a_{veg}}{A}$	a_{veg} is the total area of vegetation in a community.
Density of neighboring markets	$\sum_{j=1}^p \frac{1}{dist_{mar_j}/dist_B}$	$dist_{mar_j}$ ($dist_{hos_j}$) is the distance between a community and the j th building of the markets (hospitals) in its neighborhood circled by a searching radius of $dist_B$ (3 km). p (q) is the total number of buildings of markets (hospitals) in the searching circle.
Density of neighboring hospitals	$\sum_{j=1}^q \frac{1}{dist_{hos_j}/dist_B}$	

a higher absolute value indicates a stronger correlation. The significance test was performed by a two-tailed t-test, and the standard significance level of 0.05 was adopted. The Spearman's rank correlation analysis can inform us whether DCNCC is significantly ($p < 0.05$) influenced by a certain metric. However, the interactions between the variables were not considered in such paired correlation analysis. Therefore, subsequently, all the variables were further separately fed into two widely used multivariate regression models, the ordinary multivariate linear regression, and the stepwise multivariate linear regression. The multivariate regressions can not only help us understand the general impact (R^2) of all the urban planning metrics on DCNCC, but also show us the importance of each metric to DCNCC through the significance test results (p -value) and standardized coefficients (β) of independent variables.

4. Results and discussion

4.1 Overview of the 194 communities

The 194 communities were scattered evenly throughout Wuhan, with different CNCC and community settings (Figure 2). The CNCC for each community varies from 0 to 49 cases, with a median value of 7 cases (interquartile range, 3–12) (Table 3). The urban planning factors for each community were described by seven representative metrics (Table 2). A preliminary observation shows that communities with higher density of CNCC (DCNCC, the ratio of CNCC to the area of corresponding community) correspond to denser buildings, less percentage of vegetation, higher percentage of low-layer impervious surface areas (LSIAs), and more markets or hospitals surrounded (Figure 2). These tendencies are further demonstrated in Figure 3. For example, the area percentage of buildings in the low-

Table 3. Summary of epidemic data and urban planning metrics.

Variables	Statistics (Number of communities = 194)					
	Mean \pm standard deviation	Min	Lower quartile	Median	Higher quartile	Max
Cumulative number of confirmed cases (CNCC) (cases)	9.35 \pm 9.72	0.00	3.00	7.00	12.00	49.00
Area percentage of buildings (%)	26.20 \pm 8.09	12.50	20.30	24.92	30.67	52.41
Distance among buildings (m)	13.32 \pm 5.10	5.00	9.09	12.63	16.26	30.14
Height of buildings (m)	24.68 \pm 14.27	3.53	14.97	20.10	31.41	87.56
Area percentage of the low-layer impervious surface areas (LSIAs) (%)	53.48 \pm 14.35	1.71	45.94	56.16	62.48	78.90
Area percentage of vegetation (%)	13.27 \pm 12.87	0.00	3.18	9.08	19.11	69.21
Density of neighboring markets	17.95 \pm 21.76	0.00	6.75	12.35	24.81	217.57
Density of neighboring hospitals	165.89 \pm 258.70	3.19	65.68	126.94	173.04	3020.28

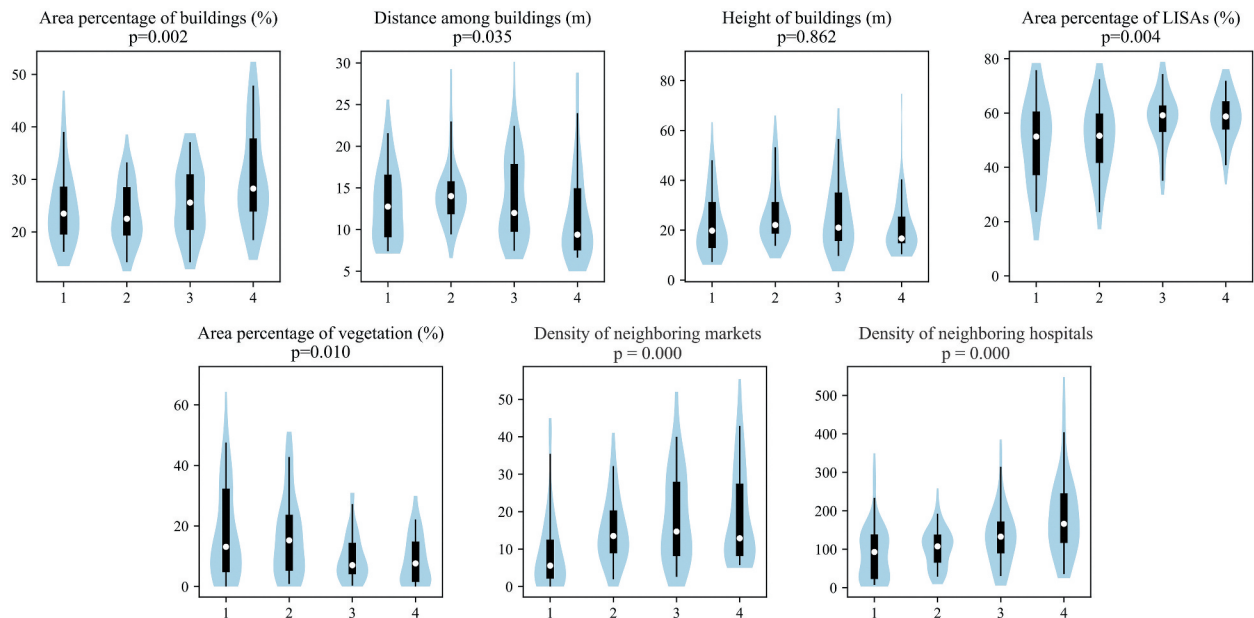


Figure 3. Violin plots of the urban planning metrics. Each metric was divided into four groups (group 1, 2, 3, and 4) according to the value of the density of cumulative numbers of confirmed cases (DCNCC, every 25% interval from low to high). The p -value is derived from the Mann-Whitney U test, which determines whether the values of group 1 (communities with low DCNCC, 0–25%) are significantly less than or greater than the values of group 4 (communities with high DCNCC, 75–100%). The white circle indicates the median value. The black box and its stretching whiskers represent the interquartile range and the range between 5th and 95th percentile, respectively. The blue shaded area shows the probability density distribution of the data, which is smoothed by a kernel density estimator. LSIAs means low-layer impervious surface areas.

DCNCC communities (median value: 22.66%, interquartile range: 20.28–28.59%), is significantly ($p < 0.05$, the Mann-Whitney U test) lower than that in the high-DCNCC communities (median value: 28.30%; interquartile range: 26.07–40.19%). Similarly, the significant differences can be also observed in other urban planning metrics, e.g., distance among buildings, and density of surrounding markets or hospitals (Figure 3). These phenomena infer that the settings of communities are possibly associated with the virus transmission.

4.2 Relationship between urban planning factors and epidemics of communities

We evaluated the relationship between DCNCC and urban planning metrics, using the Spearman's rank correlation analysis (Table 4). The results show that DCNCC is significantly and positively correlated with the area percentage of buildings ($r = 0.284$, $p < 0.001$), and the area percentage of low-layer impervious surface areas (LISAs) ($r = 0.262$, $p < 0.001$), but significantly and negatively correlated with the distance among buildings ($r = -0.191$, $p < 0.001$) and the area percentage of vegetation ($r = -0.270$, $p < 0.001$). The height of buildings does not have a significant impact ($p = 0.639$). Interestingly, DCNCC is found to have a significant and positive correlation with the density of neighboring markets ($r = 0.372$, $p < 0.001$) or hospitals ($r = 0.384$, $p < 0.001$).

The impacts of community layouts on DCNCC were further investigated by the stepwise multivariate linear regression, which can automatically select the most influential factors. Finally, two metrics, area percentage of buildings and density of neighboring markets, survived in the regression, showing their great effect on DCNCC (Table 4). Besides, the ordinary multivariate linear regression was also carried out, and the most influential factors highlighted by the ordinary regression are consistent with those chosen by the stepwise regression, which further confirmed our findings (Table 4).

4.3 Community-oriented containment strategies for combating COVID-19

Urban planning can effectively reflect the citizen's activity patterns from a micro perspective within the city, and thus poses a substantial impact on the transmission of COVID-19 in communities. Therefore, urban planning can play an essential role in prevention and control of the epidemics by curbing the relevant factors on the viral transmission. Specifically, the multivariate regression model shows that DCNCC is significantly related to the density of markets around the communities (Table 4). Many citizens of Wuhan are used to buying food (e.g., vegetables, cooked food, meats, and condiments) from markets (e.g., wet markets, supermarkets, stores). It is a tradition that the neighbors go to market together, which is beneficial for helping each other, promoting harmony, and sharing information. However, this life style seemingly became a hotbed of virus transmission during the early stage of epidemics, since markets are gathering places of residents where virus can spread easily. Therefore, closure of communities is an essential measure to reduce public contacts through markets and swiftly block the spread of COVID-19 between neighbors. During the closed-off management of communities, residents' daily necessities were purchased through group buying on the e-commerce platforms, and were then distributed to each household by community managers and volunteers who had received specialized training in epidemic prevention (Xia 2020). In this way, daily supplies for the quarantined residents were satisfied, and the risk of infection from the public contact in markets was minimized.

Another important factor highlighted by the multivariate regression model is the area percentage of buildings (Table 4). The residents in communities with high building density have more chances of mutual contacts, and thus may lead to higher risk of human exposures and infections. Our results imply that the intra-community control, e.g., prohibition of free activities within the community and quarantining

Table 4. Relationships between the density of cumulative number of confirmed cases (DCNCC) and a set of urban planning metrics.

Urban planning metrics	Spearman's rank correlation analysis		Stepwise multivariate linear regression		Ordinary multivariate linear regression	
	Coefficient	p	β	p	β	p
Area percentage of buildings	0.284	0.000**	0.440	0.000**	0.429	0.000**
Distance among buildings	-0.191	0.008*			-0.018	0.851
Height of buildings	-0.034	0.639			0.035	0.690
Area percentage of LISAs	0.262	0.000**			-0.009	0.913
Area percentage of vegetation	-0.270	0.000**			-0.048	0.611
Density of neighboring markets	0.372	0.000**	0.197	0.002*	0.190	0.004*
Density of neighboring hospitals	0.384	0.000**			-0.013	0.844

The number of communities is 194;

LISAs means low-layer impervious surface areas;

β is the standardized coefficient, indicating the relative importance of variables;

Explanatory powers (adjusted R^2) of the stepwise multivariate linear regression and the ordinary multivariate linear regression are 27.0% and 25.4%, respectively;

* Significance level at 0.01, ** significance level at 0.001 (2-tailed test).

at home, is a key measure to mitigate the risk of cross infection. This conveys an important message that during this special period, closure of communities was not enough, and the intra-community prevention measures should be adopted, especially for the high-density or high-risk residential areas. Accordingly, on 11 Feb, in addition to the closure of communities, the Wuhan government also announced that the buildings where the confirmed or presumptive cases located would be under rigorous control management. The residents in these buildings were strictly quarantined at home, and their necessities were provided specially by the community managers (Cao and Zhou 2021). Apart from the strict social distancing in each community, daily disinfection was also carried out in elevators, stairway, garbage sites, roads, and other public places of communities, by the managers and volunteers (Xia 2020). Furthermore, disposable wipes were provided in each elevator, allowing residents to operate without touching the buttons.

Some other metrics that were highlighted in the rank correlation analysis also deserve attention. Taking the density of neighboring hospitals as an example, during the COVID-19 epidemic, every hospital received a large number of suspected patients. Consequently, the risk of cross-infection would increase for the residents who were in an urgent need of medical services for other diseases and obliged to go to the nearby hospitals. The distance among buildings is also a significant factor. Smaller distance corresponds to denser distribution of buildings and more crowded residents in a community. Additionally, the distribution of buildings can influence the ventilation capacity (Yang, Qian, and Lau 2013), which is also related to the infection risk (Lee et al. 2020). However, these metrics were not captured by the multivariate regression models, possibly because of the complex interactions between all the metrics themselves.

Our findings are supported by a recently published in-situ observational study (Liu et al. 2020), which measured the concentration of airborne SARS-CoV-2 RNA in several isolated public areas of Wuhan. The authors of the study found a certain degree of viral load outside and near (about 1 meter) the entrance of a department store, and they therefore thought that the virus-laden aerosol is a possible infection source in a crowd gathering site.

4.4 Limitations

This research focused on the impacts of urban planning on the spread and control of the COVID-19 epidemic. Nevertheless, it should be pointed out that, although we found a series of urban planning factors that were significantly correlated to the DCNCC, the explanatory power for the multivariate linear

regression was not high (~ 27%, Table 4). This is understandable since remote sensing and urban planning can only evaluate the evolution of the epidemics according to people's overall behaviour patterns. More sophisticated prevention and control measures should depend on comprehensive testing and tracking of the infected people as well as their close contacts.

Secondly, the number of communities included in this research is 194, which is not large. This is because only a part of communities released the number of confirmed cases, and the time to publish the information was not consistent among different communities. In addition, these communities did not release and update the data continuously. More importantly, we used a time window of three-days to further screen the communities, since a larger window would lead to an unfair comparison between communities and irrationality of the modelling. Meanwhile, we did not select the communities that released the data before 12 Feb (the revision of the diagnostic criteria led to 13436 cases added overnight), owing to the insufficiency of the statistics. Finally, we chose the time span during 12 and 14 Feb, in order to maximize the number of communities available.

Finally, some technical limitations of this study need to be addressed here. (1) The land cover data were derived from the high-resolution remote sensing images acquired on October 2018, which did not exactly coincide with the epidemic data in terms of time (February 2020). Considering the rapid urbanization in Wuhan, the land cover within/around the selected communities (Figure 2) might have changed slightly from October 2018 to February 2020, which could cause bias to the calculated urban planning metrics. (2) The urban planning metrics used in this study were derived from the static land cover maps, which are related to citizen's activity patterns, but cannot provide the dynamic information on human mobility. Compared to urban planning metrics, the human mobility information is expected to be superior in reflecting the movement and mutual contact of residents. However, it is very difficult for us to obtain the fine-grained human mobility data within Wuhan at the early stage of the outbreak. With the development and application of some contact-tracing apps (Sharma et al. 2020; Trang et al. 2020), future studies can try to make a more comprehensive analysis of the spread pattern of COVID-19 within the city by using the fine-scale tracking data of residents.

5. Conclusions

Currently, most of the existing studies focused on the importance of Wuhan's lockdown in containing the early outbreak in other cities (Chinazzi et al. 2020; Kraemer et al. 2020; Lau et al. 2020; Tian et al. 2020). However, another remarkable intervention measure,

the close-off management of communities, has not received sufficient attention yet. In this study, therefore, we addressed this important issue from the perspective of remote sensing and urban planning. Our results confirmed the significant correlation of some urban planning factors to the epidemic of Wuhan, based on which, we analyzed the rationality and effectiveness of the community-oriented containment measures. Currently, the situation of COVID-19 epidemics is very rigorous across globe. In spite of the differences in the policies and cultures among different regions, we call for the managers of cities to adopt community-oriented prevention and control measures in terms of the local conditions. Moreover, the experiences of Wuhan (a metropolis with over 10 million residents) in combating the COVID-19, suggested the important role of communities in future urban planning and management, e.g., preparedness of infectious diseases, construction of health city (Lawal and Anyiam 2019; Zhu et al. 2019).

Disclosure statement

No potential conflict of interest was reported by the authors.

Data availability statement (DAS)

The data that support the findings of this study are available from the corresponding author [X. Huang], upon reasonable request.

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