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Quantifying COVID-19 recovery process from a human mobility perspective: An intra-city study in Wuhan

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ABSTRACT

The COVID-19 pandemic has brought huge challenges to sustainable urban and community development. Although some recovery signals and patterns have been uncovered, the intra-city recovery process remains underexploited. This study proposes a comprehensive approach to quantify COVID-19 recovery leveraging fine-grained human mobility records. Taking Wuhan, a typical COVID-19 affected megacity in China, as the study area, we identify accurate recovery phases and select appropriate recovery functions in a data-driven manner. We observe that recovery characteristics regarding duration, amplitude, and velocity exhibit notable differences among urban blocks. We also notice that the recovery process under a one-wave outbreak lasts at least 84 days and has an S-shaped form best fitted with four-parameter Logistic functions. More than half of the recovery variance can be well explained and estimated by common variables from auxiliary data, including population, economic level, and built environments. Our study serves as a valuable reference that supports data-driven recovery quantification for COVID-19 and other crises.

1. Introduction

Our world is threatened by a massive health crisis from the coronavirus disease 2019 (COVID-19), which has dramatically changed every aspect of our society. Cities with a high concentration of population, goods, and culture suffer from severe blows and are the ground zero in this pandemic (UN, 2020a). People have to alter their routine behaviors, postpone or even cancel non-essential travels; businesses are heavily interrupted and hard to operate; plenty of schools have transformed from face-to-face teaching to online classes. These pronounced changes in the city rhythm have brought great challenges to realizing sustainable development goals (Elavarasan et al., 2022; UN, 2021a).

Recovery from the COVID-19 pandemic is an issue of vital importance for global cities. Nowadays, many recovery plans have been placed on the agenda to help cities get back on track (EC, 2020; OECD, 2020; UN, 2020b, 2021b; WEF, 2020a; whitehouse.gov, 2021). A common thread in these plans is seeing the epidemic recovery as an opportunity to build back better, stronger, greener, and more inclusive. As growing recovery signals are found on multisource data, it is urgent to carry out quantitative analysis to provide further decision-making support (Zhang, Feng, et al., 2021). At the same time, existing investigations have shown that the COVID-19 impact is a spatially, socially, and economically heterogeneous matter within the city (Hou et al., 2021; Kissler et al., 2020; Huang, Lu, et al., 2022). Thus, it is necessary to pay close attention to the intra-city recovery to promote public welfare and social equity.

Fortunately, the human mobility perspective offers us great access to quantify city recovery. For one thing, people always perceive their surroundings and urban dynamics in a sensitive manner, so the movement information changes more intensely and frequently than other traditional indicators. Existing researches have confirmed that the mobility indicator has prominent advantages in terms of reflecting epidemic situations (Pan et al., 2020; Xiong et al., 2020), evaluating control measures (Kraemer et al., 2020; Lai et al., 2021; Wellenius et al., 2021).
2. Related works

2.1. Definition of recovery and its characteristics

The concept of recovery in this study refers to the process of a system returning to a normal state after being hazard-attacked. The Sendai Framework for Disaster Risk Reduction (2015–2030) takes recovery as one of four priorities for action, where recovery is not only the goal of sustainable development and “build back better” but also the basis for avoiding or reducing future disaster risk (UNDRR, 2017). In the disaster management cycle, recovery is placed at the intermediate position between response and mitigation (Sarker et al., 2020). In particular, most common disasters are characterized by a rapid strike and slow adaptation, leading to the recovery process often receiving an independent focus (Yang et al., 2018). In the resilience topic, recovery is seen as an essential property (Brunet et al., 2003; Hosseini et al., 2016; Zhou et al., 2019). The uniqueness of the recovery process is that people can directly participate in the construction and influence the outcome, thus bringing great significance to resilience improvements (Kotani et al., 2020). In general, existing knowledge and relevant theories consider recovery as a multi-dimensional process that mainly consists of two key elements.

One key element is the recovery phase which reflects time costs when a system recovers from disasters. The recovery phase is determined by the recovery’s start time and end time, and it can be quantified by the arrival of an equilibrium state. Sometimes the final state may be lower or higher than the original state (Wang, Yang, et al., 2014). Identifying the recovery phase requires continuous or multiple observations, so it highly depends on data acquisition conditions. For a long time, follow-up surveys (Wang, Li, et al., 2014; Stringfield, 2010), repeat photography (Burton, 2015), and field visits (Contreras et al., 2018) are the main approaches for recovery phase division. In recent years, mobile phone data has become a popular source due to its advantages of real-time recording, wide spatial coverage, and no interference with objects (Hong et al., 2021; Wu et al., 2021; Yabe, Tsubouchi, Fujiwara, Sekimoto, et al., 2020). Sufficient observations are conducive to informing the accurate recovery phase, especially when there is a comparable normal baseline.

The other key element is the recovery function that reflects morphological changes when a system recovers from disasters. The recovery function is determined by curve equations, and it can be quantified by the parameter characteristic that includes amplitude and velocity. The recovery function usually takes time information as the independent variable, while its dependent variable is diverse, which can be the absolute quantity (Adams et al., 2012), the normalized index (Yang et al., 2018), or the probability value (Liu et al., 2022). The function category depends on the form abstracted degree. The recovery process has a continuous rising feature in the most well-known model (Brunet et al., 2003). This description has been widely recognized and applied in subsequent analyses where recovery is expressed by the linear function with a positive slope (Pantelli et al., 2017; Qiang et al., 2020; Adams et al., 2012). However, many researchers find that the actual recovery process varies at different stages, thus demanding the usage of nonlinear functions (Murao & Nakazato, 2010; Murao, 2020; Wang, Li, et al., 2014; Dikmen et al., 2020; Baroud et al., 2014; Zhu et al., 2017). Either way, the selection of specific functions remains to be a difficult task.

At present, comprehensive consideration of the above recovery elements is highly recommended and attracts growing interest (Liu et al., 2022; Kotani et al., 2020; Yabe, Tsubouchi, Fujiwara, Sekimoto, et al., 2020; Liu, Gerber, et al., 2021; Zhu et al., 2017; Qiang et al., 2020; Burton, 2015), as such element combination corresponds to the multidimensional essence of the recovery process.

2.2. Recovery from epidemics

Some great efforts have been devoted to revealing the epidemic recovery process. Recovery signals are found in various data categories, such as economic statistics (WEF, 2020b), bank card transactions (Yang et al., 2020), electricity consumption records (Wang et al., 2021), remote sensing images (Tao et al., 2020), and social media data (Wang et al., 2022). However, since the COVID-19 recovery is a long and slow process, many observed indicators have not entirely recovered and still need time to be tracked. Furthermore, due to the confined data resolution, most researchers only focus on the county, provincial, or national levels, largely ignoring the intra-city recovery disparity. Fortunately, the Data for Good initiative during the COVID-19 pandemic brings solutions to the abovementioned difficulties. Among diverse spatiotemporal data, human mobility data has been widely recognized to own unique value in helping fight COVID-19 (Alessandretti, 2022; Buckee et al., 2020; Grantz et al., 2020). Prominent efforts have been made to introduce human mobility perspectives to the intra-city scale recovery. Recovery patterns are discovered in dwelling and working behaviors (Liu, Pei, et al., 2021), among sociodemographic factors (Eom et al., 2022), and at different spatiotemporal levels (Huang, Xu, et al., 2022; Dong, Sun et al., 2022).

However, the epidemic recovery research is still underexplored compared to the abundant number of COVID-19 literature. The reason is that epidemic has challenged the empirical recovery paradigm from traditional disasters (Fakhruddin et al., 2020; Zhang, Feng, et al., 2021). First, the epidemic recovery phase is vague to identify. Regarding the start time, the same long impact phase makes it hard to distinguish recovery from pre-recovery. Regarding the end time, due to the absence of comparative baselines and referential criteria (Ho et al., 2021), most studies fail to judge when recovery is fully completed nor confirm whether a final state has been achieved during the study period. Second, there is no consensus on the morphological feature of epidemic recovery functions. As cities undergo frequent outbreaks (UN, 2022), difficulties exist to separate a clear recovery form from many mixed interferences.

In summary, epidemic recovery research can be advanced from the following aspects. First, the potential of human mobility in monitoring
urban epidemic recovery should be further explored. Second, a typical case study with the complete recovery process is urgently needed to reveal essential characteristics of the recovery from COVID-19 and other epidemics.

3. Study area and data collection

3.1. Study area

As the first city with proactive interventions, Wuhan effectively controlled the COVID-19 epidemic after a lockdown (Tian et al., 2020; Xin et al., 2021) and achieved a rapid resumption without new waves (Cao et al., 2020; Xinhuanet, 2021) (Fig. S3). Therefore, its recovery is a scenario free from other potential interferences and can reveal some unique characteristics of the epidemic recovery process. Wuhan is the provincial capital city of Hubei and an important regional hub in Central China. Due to its convenient location, Wuhan has attracted many companies, factories, universities, and institutions. According to the Seventh National Census, Wuhan had 12.32 million residents at the end of 2020, with 1.93 million rural population and 10.39 million urban population. Wuhan implemented a lockdown from January 23, 10:00 am to April 8, 0:00 am in 2020. Fig. 1 (b) shows that our study area, a region within the Third Ring Road, contains the most confirmed cases. According to Fang (2019), our study area comprises a high degree of urbanization and can be divided into 101 blocks (Fig. 1 (c)).

3.2. Data collection

Aggregated mobility data was derived from Baidu, one of the largest Internet companies in China. The data contains hourly mobility grids from January 1, 2019, to January 1, 2021, and is collected from location-based services that integrate substantial smartphone applications, such as map navigation, online search, and e-shopping. Acquisition methods include global positioning system, IP address, signaling tower, and WIFI. After obtaining users’ consent, the anonymous trajectory is recorded in real-time and then aggregated in a 200 m grid each hour (Fig. 2). For maximum privacy protection, the service provider deleted those grids with less than ten people.

Due to high market penetration and extensive user coverage, the mobility data from Baidu is featured by its representativeness and the capability to depict population distribution (Fang et al., 2020; Feng et al., 2019). The mobility data from Baidu has been used in a variety of fields, including government management (youth.cn, 2020), urban planning (Li et al., 2019; Fan et al., 2021), and disaster rescue (Lin et al., 2020). In addition, many case studies in Wuhan also utilize such data (Wang, 2018; Lin et al., 2020; Lyu & Zhang, 2019; Zhang & Li, 2019), well validating its effectiveness in reflecting population dynamics (Lyu & Zhang, 2019).

Reported case data was obtained from the Wuhan Municipal Health Commission website (http://wjw.wuhan.gov.cn/ztzl_28/fk/tzgg/). According to China’s official epidemic prevention and control phase (http://www.gov.cn/zhengce/2020-06/07/content_5517737.htm), the number of newly confirmed cases can effectively indicate changes in the COVID-19 situation. Thus, we used the daily new case number at the district level (the finest scale of case data publication). A block was assigned to have the same daily new case trend with the district where it is located.

Multisource auxiliary data were used to form an independent variable pool for recovery characteristic models. We followed a previous Wuhan epidemic study (Gao et al., 2022) to set categories, including demographic data, socioeconomic data, and built environment data. For each category, we selected variables confirmed to be related to COVID-19 mobility by existing literature (Huang, Lu, et al., 2022; Li et al., 2020; Xia et al., 2020; Liu, Pei, et al., 2021). A total of 35 variables were finally selected, and their descriptive statistics can be found in Table 1. Detailed information regarding their sources can be found in Supplementary materials.

Fig. 1. Cumulative confirmed cases in (a) China and (b) Wuhan as of January 1, 2022. (c) A total of 101 blocks within the Third Ring Road in Wuhan.
4. Methodology

4.1. Overall framework

Fig. 3 shows the overall framework of this study. Based on the above review and research gaps, we determine to make improvements in four directions. Specifically, we want to design a comprehensive quantitative approach, which focuses on key recovery elements in the existing theory, takes emerging mobility data into account, and adds new features from the COVID-19 epidemic context, aiming to reveal essential characteristics of the intra-city recovery through a complete one-wave process. We hope this approach can complement the epidemic recovery research and benefit the applications of human mobility information in this post-pandemic era.

4.2. Approach design

Our approach includes four procedures (Fig. 4): (1) processing mobility sequences, (2) identifying recovery phases and calculating durations, (3) selecting recovery functions and fitting parameters, and (4) modeling recovery characteristics. The details of each procedure are introduced below.

4.2.1. Step 1: processing mobility sequences at the block level

First, we chose the daily mobility count as the observed indicator for measuring recovery process. To eliminate intra-day variations caused by device switching and WIFI changing, we summed 24-hour mobility grids to obtain the one-day summary. Note that the mobility count used here is not equivalent to the number of people but indicates the quantity of population movements exceeding the recognizable distance threshold (i.e., the positioning accuracy). For example, a person who moves...
frequently will have a larger value than a person who does not move that often.

Next, to reduce the weekly periodic noise, we implemented a seven-day window and adjacent average method to smooth block mobility sequences. We also filtered the local fluctuation caused by national holidays (Fig. S2) for sequence stabilization. Since daily information was smoothed and filtered out, we chose a two-week interval as the minimum unit and took Sunday as the unified benchmark (Fig. 5) for the subsequent recovery phase identification. Although the above procedure discretized specific dates, it provides a robust solution to make mobility sequences of different years comparable on the same day.

4.2.2. Step 2: identifying recovery phases and calculating durations

Based on existing studies (Dong, Sun, & Zhang, 2022; Eom et al., 2022; Huang, Lu, et al., 2022; Liu, Pei, et al., 2021), we used four criteria to identify the recovery phase: newly confirmed cases, mobility sequence slope, mobility quantity baseline, and mobility spatial pattern baseline (calculated by Moran’s I statistics of daily mobility grids). Specifically, newly confirmed cases and mobility sequence slope are used to determine the recovery start time, while two mobility baselines are used to determine the recovery end time. Then, the recovery
duration equals the number of days between start and end times.

The recovery start time should satisfy the following requirements: (1) after the virus spread is under control (i.e., the daily new case number shows a descending pattern) and (2) after the population activity begins to rise (i.e., the mobility sequence slope shows an increasing pattern). The recovery end time should satisfy: (1) no earlier than reaching the mobility quantity baseline and (2) no earlier than reaching the mobility spatial pattern baseline. To judge recovery completion, a comparable baseline is crucial for the ever-changing mobility indicator. In this study, we used the multiplication of contemporaneous value in the pre-pandemic year (i.e., the year 2019) and one-year mobile phone growth rate as a theoretical expectation.

4.2.3. Step 3: selecting recovery functions and fitting parameters

We applied the best function selection and curve fitting methods for recovery parameterization. First, a total of 64 commonly used functions with generally increasing trends were selected to build a candidate set (Table S1). These functions can be classified into seven categories, i.e., Polynomial, Waveform, Exponential, Sigmoidal, Logarithm, Piecewise, and Power. Second, the Levenberg-Marquardt algorithm (Pujol, 2007) was used for fitting optimization. The iteration number was set to 400, and the Chi-Square tolerance was set to 1e-9. With the goal to minimize Reduced Chi-Square, iteration calculations were performed until the optimal parameter value was obtained. Third, six goodness-of-fit indexes were used for functions comparison, including convergence success count (CSC), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Adjusted R-Square (Adj. $R^2$), Residual Sum of Squares (RSS), and Reduced Chi-Square (RSS/DOF, where DOF denotes Degree of Freedom). The final best function was decided based on the equal-weight ranking (Rank) of these six indexes.

4.2.4. Step 4: modeling recovery characteristics with critical variables

Finally, we used multisource auxiliary data to model recovery characteristics and determine critical variables. Two types of recovery elements were presented for dependent variables. As recovery durations are of the discrete type, the decision tree classification was used together with the grid search algorithm for criterion (either "gini", "entropy", or "log loss"), the maximum depth of trees, and the minimum number of samples required to split an internal node. As recovery function parameters are of the continuous type, the multiple linear regression was used together with the stepwise algorithm. All independent variables were at the block level. Finally, we selected the best model with statistically significant variables to explain the epidemic recovery process, aiming to provide an efficient estimation scheme.

5. Results

5.1. Recovery phases and durations

Fig. 6 provides a holistic view of our proposed approach and shows a complete one-wave recovery process at the city level. Under the four criteria, we identify an incremental recovery spanning 112 days. From the recovery start time (March 1, 2020), the daily new case number continues to decline while the mobility sequence slope begins to increase. From the recovery end time (June 21, 2020), the daily mobility curve not only reaches the quantity baseline (afterward, it exceeds baseline because mobility counts decline in the summer vacation under normal states) but also keeps pace with the Moran’s I baseline. As for spatial distributions, we observe notable differences between start and end times, suggesting the presence of recovery disparities within our study area.

Fig. 7 shows the block-level recovery duration with a statistical histogram and spatial distribution. Fig. 7 (a) indicates that recovery start times are considerably more synchronous than recovery end times. Concretely, a total of 101 recovery processes simultaneously start from March 1, 2020, but end on six different dates (i.e., May 24, June 7, June

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**Fig. 6.** The city-level recovery process, including daily mobility sequences, four recovery phase criteria, and spatial distribution maps.
21, July 5, August 2, and August 30). The shortest recovery duration is only 84 days, while the longest is 182 days. Additionally, recovery durations in 60% of blocks are shorter than the city-level duration (112 days), and those in 31% of blocks are longer. Fig. 7(b) shows the spatial distribution of durations among the investigated 101 blocks. Despite a few exceptions, blocks in western Wuhan generally recover quicker than those in eastern Wuhan. Moreover, blocks with similar durations are likely to cluster together, revealing a notable spatial clustering pattern.

5.2. Recovery functions and parameters

Table S3 in Supplementary materials shows the fitting result of the city-level recovery. Among 64 commonly used recovery functions, 43 functions successfully converge. According to goodness-of-fit indexes, the Logistic function offers the best performance with the lowest AIC, BIC, RSS, RSS/DOF, and the highest Adj. \( R^2 \). Besides, LangevinMod, SWeibull2, DoseResp, and Boltzmann also have good performances and can be considered as effective alternatives. It is worth noting that the Sigmoidal category shows dominant advantages among top-ten functions. The remaining four functions belong to Exponential, Waveform, Polynomial, and Piecewise. These results suggest that our study area has an evident nonlinear recovery process.

Table S4 in Supplementary materials shows the fitting result of the block-level recovery, and Fig. 8 shows the result from selected functions. For each block, the best recovery function was obtained according to the equal-weight ranking (Rank). Fig. 8(a) shows that 101 blocks have seven best choices. These selected functions are also at the top of Table S3, reflecting that the block-level recovery presents a relatively consistent pattern with the city-level recovery. Moreover, the Logistic function is the best choice for 74 blocks, reflecting that most blocks have a relatively unified recovery form. For each function, the average goodness-of-fit index of all blocks was calculated to verify its fitting performance (Table S4). The radar chart of seven selected functions is shown in Fig. 8(b). It can be seen that the Logistic function has the highest ranking among all six indexes, exhibiting its superiority over other functions.

According to the above results, the Logistic function is confirmed to have an absolute advantage over other competing functions and the highest fitting performance among most blocks. Its mathematical equation is as follows:

\[
y(x) = \frac{A_1 - A_2}{1 + \left(\frac{x}{x_0}\right)^p} + A_2
\]

where \( x \) is the number of days after the start time, and \( y(x) \) is daily mobility counts. \( A_1, A_2, x_0, \) and \( p \) denote initial value, final value, center location, and power, respectively. Specific meanings of these four parameters are as follows: (1) the lowest level of daily mobility counts \( (x=0, y(x)=A_1) \); (2) the highest level of daily mobility counts \( (x\to\infty, y \to A_2) \).
(x)→A_2); (3) days when mobility counts grow by half level (x=x_0, y (x)=A_1+Ax_0); and (4) the mobility growth steepness. On the whole, A_1 and A_2 control the recovery amplitude while x_0 and p control the recovery velocity.

For the city-level recovery, fitted values of A_1, A_2, x_0, p with the processed mobility sequence are 967,374, 2,277,926, 46.93, and 3.21. Although A_1 and A_2 are asymptote levels in mathematics, we notice they are generally close to mobility counts at start time (972,238) and end time (2,268,273). x_0 corresponds to April 17, 2020, one week after Wuhan lifted the lockdown (April 8, 2020). For the block-level recovery, fitted values of 99 successfully converged blocks are shown in Fig. 9. It can be seen that four parameters present strong heterogeneities among different blocks, even if the division standard was adjusted to make amplitude parameters (A_1 and A_2) as well as velocity parameters (x_0 and p) equal in block numbers at each class. These inconsistent spatial distributions indicate that each Logistic parameter carries unique information to shape the block-level recovery process.

For the amplitude parameter, high values of A_1 are distributed without notable directivity, while high values of A_2 are distributed following an east-west direction and perpendicular to the Yangtze River. Such spatial differences signify a great mobility change during the recovery phase. For the velocity parameter, spatial distributions of x_0 and p are globally similar but exhibit some local diversities. In Fig. 9, blocks with faster and slower velocities than the city-level recovery are denoted in blue and red, respectively. We observe that two velocity parameters present a prominent stratified structure: blocks located on the city edge recover quickly, evidenced by their small x_0 and large p, while blocks in the city center recover slowly, evidenced by their large x_0 and small p.

5.3. Recovery characteristic models

Fig. 10 shows the recovery duration model employing decision tree classification and grid search algorithm. With the optimal hyper-parameter combination, the learning accuracy of the final best model is 78.22 %, and the accuracy of ten-fold cross-validation is 63.36 %. Among six durations (Fig. 7), the most accurate category is the duration of 84 days, with 37 (out of 38) successfully classified blocks, followed by the duration of 98 days, with 19 (out of 23) successfully classified blocks, and the duration of 182 days, with 12 (out of 17) successfully classified blocks. The decision tree extrapolates seven critical variables and their branch conditions to the recovery duration. For example, a block with an education area \( \leq 0.765 \text{ km}^2 \), house price \( \leq 19,480 \text{ RMB/m}^2 \), and hotel number \( \leq 146 \) is highly likely to have a recovery duration of 84 days. We notice that the education area is the most critical variable, given its root node position in our decision tree. Further calculations show that the education area contributes to 25.3 % of the model prediction, followed by house price (21 %), hotel number (18 %), commerce area, asset amount, traffic area, and culture number.

Table 2 shows four models of the recovery function parameter using multiple linear regression and stepwise algorithm. The best model is able to explain 92 % of the A_2 variance through five critical variables, and the last model can also explain half of the p variance, proving the well establishment of our regression models. Durbin-Watson values (usually between zero and four) are close to two, meaning that observations meet the mutual independence prerequisite. There is no multicollinearity among selected variables since all variance inflation factor (VIF) values are less than three. From the combination of critical...
variables and their coefficients, we obtain the regression equation for each Logistic parameter. Notably, coefficients consider the magnitude effect: when a variable has small values, such as land use areas, its coefficient will be large, and vice versa.

The comparable effect among different critical variables can be found by the standard coefficient. Specifically, medicine number plays a most important role in explaining the difference of \( A_1 \), while hotel number occupies a primary position for the other function parameters. These results illustrate distinct facility usages during the city recovery phase. Moreover, population and asset amount are variables that appear several times, meaning the demographic and economic levels are associated with the recovery process on multiple dimensions. In addition, a negative correlation between \( A_2 \) and nighttime light stems from the fact that L11-01 data are sensitive to street lamps, spot illumination, and strong lighting in docks and factories. The other three negative effects in \( x_0 \) and \( p \) suggest that the more hotels and the fewer population, the slower the recovery velocity.

Fig. 10 shows the spatial distribution of nine critical variables in four regression models. We observe no noticeable positive or negative correlation among these variables. Generally, blocks with large POI numbers in medicine, hotel, and finance are mostly distributed in the urban center; blocks with large residential areas and large population are located in the middle transition zone; blocks with an extensive industrial area are mainly in the external layer. By comparison, spatial distributions of asset amount and recreation area are rather scattered. These results display representative intra-city traits of population,
5.4. Recovery pattern verification

In this section, we present verification of the mined recovery elements. We mainly focus on time-related recovery characteristics to explore whether the human mobility information is sensitive, accurate, and effective in the epidemic recovery process.

The recovery duration was obtained via four criteria before the Logistic function parameterization. Fig. 12(b) shows that half-duration has the largest minimum value and the widest quartile interval, revealing that blocks in Wuhan recover at a fast pace in the front phase and change to a slow pace in the later phase. According to our classification model, the education area is the most critical variable for explaining the longest 182-day duration. This result echoes the fact: many colleges and universities are located east of the Yangtze River and around South Lake; the face-to-face classroom was postponed until September (bendibao.com, 2020), making low mobility counts in the 2020 spring semester.

The center location parameter, $x_0$, represents days when mobility counts increase by half of the recovery amplitude. Its minimum value is 37.69, corresponding to April 8, 2020, when Wuhan lifted the lockdown and allowed cross-region flows (chinanews.com, 2020; Xinhuanet, 2020b). Before this date, no block achieved half amplitude, even though Wuhan’s traffic, business, and production had resumed in March (Chinadaily, 2020; cnr.cn, 2020; Hubeidaily, 2020; Xinhuanet, 2020a). This phenomenon confirms that external traffic reconnection is a great driving force for promoting recovery magnitude. Additionally, 50% of $x_0$ fall in the range between 42 and 53 (corresponding to April 12 and 23), reflecting that many population activities started to increase within 11 days after the lockdown lifting.

The power parameter, $p$, controls the curve steepness of the Logistic function. Although $p$ does not directly correspond to time, it helps to derive the fastest growth day ($x_1$) by combining with $x_0$. As an S-shaped curve, the Logistic function reaches its largest slope at the turning point. Hence, we can solve the second derivative (let $y(x_1)^\prime\prime = 0$) to obtain $x_1$:

$$x_1 = x_0 \sqrt{\frac{p - 1}{p + 1}}$$

(2)

where the combination of $x_0$ and $p$ yields a new time-related parameter ($x_1$). Fig. 12(c) shows that $x_1$ also has a stratified structure, but it is significantly different from that in Fig. 9. According to Fig. 12(b), $x_1$ has the smallest value and the most concentrated range. Its mean and median both correspond to April 8, 2020, and its quartile interval is only five days. These results demonstrate that half of blocks in Wuhan present positive responses to the external traffic reconnection within one week. Notably, both the first and last values of $x_1$ signify key events: the minimum value (13.6) corresponds to March 14 when the daily new case number in Wuhan dropped to single digits (gov.cn, 2020); the maximum value (63.0) corresponds to May 3, a national holiday with high population flows.

6. Discussion

6.1. The proposed approach: a promising connecting bridge

The advantages of our proposed approach are twofold. First, at the theoretical level, our approach corresponds to the research trend of considering multi-dimensional recovery characteristics with key recovery elements. We also include epidemic-related features to understand the impact of COVID-19, benefiting the development of responding plans. Second, at the applicable level, our approach offers valuable references for future epidemic recovery research. We use the number of COVID-19 cases and space-time constraints to identify the recovery phase, which alleviates the recovery illusion due to social-distancing fatigue (Shearston et al., 2021). We also use broad form options to solve the difficulty in selecting recovery functions (Murao & Nakazato, 2010). We believe those four criterion alternatives (see Section 4) and 64 potential curves (see Section 5) in Supplementary materials are sufficient to describe numerous recovery situations. For recurrent outbreaks, our approach still has great flexibility, as some scholars have found that multi-wave complex results can be built by superimposing a one-wave process (Han et al., 2021).

Meanwhile, our proposed approach verifies the effectiveness of
relying on human mobility perspectives to quantify the recovery process. We notice that population movement corresponds well with resumption policies, usually presenting rapid responses that characterize human activities (Hunter et al., 2021; Rodríguez González et al., 2021). The turning point of mobility sequences accurately corresponds to actual events such as traffic reconnection and lockdown lifting. Thus, we encourage scholars to expand human mobility applications into the epidemic recovery investigation. During the COVID-19 pandemic, human mobility perspectives have been included in control measures evaluation (Kraemer et al., 2020; Lai et al., 2021; Wellenius et al., 2021), economic loss estimation (Yang, Wei, et al., 2022), infectious disease modeling (Chang et al., 2021; Hou et al., 2021), and crash hazard modeling (Dong, Zhang, et al., 2022). Our approach further incorporates this perspective into the recovery process quantification and proves its effectiveness in monitoring the intra-city recovery timeline.

6.2. Urban management implications

This study reveals the essential recovery process in a typical city with a complete one-wave epidemic. Learning from existing experience is valuable for facilitating decision-making and promoting resumption. Here, we provide urban planners and managers with suggestions based on two key recovery elements (Table 3).

![Figure 12](image-url)

**Table 3**

A summary of critical policy implications.

| Key element       | Main finding                                                                 | Enlightenment                                                                 | Guide to action                  |
|-------------------|------------------------------------------------------------------------------|------------------------------------------------------------------------------|----------------------------------|
| Recovery phase    | Duration time is at least 12 weeks.                                          | • COVID-19 is the greatest barrier to city operations in China.               | • Recognizing that COVID-19       |
|                   |                                                                              | • Long-term downturn brings enormous economic losses.                        | epidemic is a new type of         |
|                   |                                                                              |                                                                              | catastrophe.                     |
|                   |                                                                              |                                                                              | • Accelerate and persist diverse |
|                   |                                                                              |                                                                              | resumption promotion measures.    |
| Recovery function | Logistic function in the Sigmoidal category is the best choice, similar to | • Recovery heterogeneities widely exist in time and space.                    | • Implement phased and targeted  |
|                   | common disasters.                                                            |                                                                              | recovery strategies.             |
|                   |                                                                              | • Recovery form has strong stability and similarity.                          | • Establish an integrated multi-  |
|                   |                                                                              |                                                                              | hazard framework.                |

Fig. 12. Time-related recovery characteristics: (a) the Logistic function schematic; (b) boxplots of half-duration, x₀, and x₁ (note: to display data clearly, we removed x₀ with above 100); (c) the spatial distribution of x₁ (division standard is consistent with x₀ and p).
First, authorities need to discern that the COVID-19 epidemic is a new type of catastrophe for urban development. Relying on sufficient data and robust criteria, we find the shortest recovery duration is 84 days in Wuhan. This recovery duration is much longer than frequent local floods, which last only several hours or days (Liu, Yang, et al., 2021). We encourage governments to develop resumption measures to assist cities rebound from COVID-19. Infectious diseases do not cause physical damage like natural disasters, but they bring functional disruptions to transport networks, commercial services, and social activities. Especially in this close-cooperation era, the pandemic impact can spread to whole industrial chains and numerous associated areas (Yang, Chen, et al., 2022). Authorities must be aware of these severe consequences and learn from existing cases to prevent COVID-19 from evolving into a “gray rhinoceros” event with huge losses.

Second, stakeholders should leverage the S-shaped function in recovery policy formulation. Cities need to create a dynamic priority list following the S-curve feature. The result from Wuhan indicates that recovery heterogeneities widely exist among different subareas and during various stages. Specifically, policy attention should be first paid to places with medical services and material productions for supporting their operations, and then turn to hotels, recreation sites, and finance facilities because their high population activities mean high virus transmission risk and may bring case resurgence. In addition, cities can utilize the stability and similarity in S-curve recovery to establish an integrated framework for various crises. From our results, the Logistic function is the best selection. Previous investigations under different hazards also show recovery possesses an explicit S-shaped form (Murao & Nakazato, 2010; Wang, Li, et al., 2014; Zhu et al., 2017; Dikmen et al., 2020; Han et al., 2020; Murao, 2026; Baroud et al., 2014). These findings provide a practical basis for integrating the public health emergency into the existing natural disaster framework, thus facilitating the establishment of a multi-event assessment system in the future.

6.3. Contributions and limitations

Our contributions lie in three aspects. First, we design a new approach to consider key recovery elements under the COVID-19 context, filling the research gap in epidemic recovery and responding to current calls for recovery quantification. Second, we reveal essential characteristics of the COVID-19 recovery through a complete one-wave process. This study marks a pioneering effort to show intra-city recovery disparities without multi-wave interferences. Third, we prove the effectiveness of human mobility in modeling the recovery process, enriching big data applications to track and combat COVID-19.

The COVID-19 recovery process is a complex issue, and we recognize some limitations of this study. First, although human mobility effectively indicates the recovery process, some crucial dimensions like psychological signals (Fu et al., 2020; Sampogna et al., 2021) are not reflected. More efforts are needed to explore these underexploited dimensions. Second, as our mobility data was aggregated in 200 m grids, it is difficult to measure individual behaviors during different recovery stages, such as the social contact transformation (Yabe, Tsubouchi, Fujiwara, Wada, et al., 2020; Zhang et al., 2020; Zhang, Litvinova, et al., 2021). We encourage future efforts to leverage refined human mobility data with detailed trajectory and flow directions.

7. Conclusion

The COVID-19 pandemic has tremendously impeded sustainable urban development. Although recovery signals and patterns have been uncovered, intra-city complete results remain limited. To fill this gap, we propose a comprehensive approach to quantify COVID-19 recovery leveraging fine-grained human mobility records. Taking the city of Wuhan as our study area, we reveal the recovery process for its 101 blocks by identifying accurate recovery phases and selecting appropriate recovery functions in a data-driven manner. Our results point to the distinct disparity among urban blocks in terms of multiple recovery characteristics regarding duration, amplitude, and velocity. We also find that the recovery process under a one-wave outbreak lasts at least 84 days and has an S-shaped form best fitted with four-parameter Logistic functions. More than half of the recovery variance can be well explained and estimated by common variables from auxiliary data, including population, economic level, and built environments. The conceptual, methodological, and applicable knowledge of this study can serve as valuable references that support data-driven recovery quantification for COVID-19 and other crises.

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CRediT authorship contribution statement

Xiaoyan Liu: Conceptualization, Methodology, Investigation, Writing – original draft. Saini Yang: Conceptualization, Writing – review & editing, Project administration. Xiao Huang: Methodology, Writing – review & editing. Rui An: Investigation, Resources, Validation. Qianguang Xiong: Investigation, Resources. Tao Ye: Writing – review & editing, Funding acquisition.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary materials

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2022.104104.

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