# Traffic Density Reduction Caused by City Lockdowns Across the World During the COVID-19 Epidemic: From the View of High-Resolution Remote Sensing Imagery

Chen Wu, Member, IEEE, Sihan Zhu<sup>®</sup>, Jiaqi Yang<sup>®</sup>, Student Member, IEEE, Meiqi Hu, Bo Du<sup>®</sup>, Senior Member, IEEE, Liangpei Zhang<sup>®</sup>, Fellow, IEEE, Lefei Zhang<sup>®</sup>, Senior Member, IEEE, Chengxi Han, Student Member, IEEE, and Meng Lan, Student Member, IEEE

Abstract—As the COVID-19 epidemic began to worsen in the first months of 2020, stringent lockdown policies were implemented in numerous cities throughout the world to control human transmission and mitigate its spread. Although traffic density reduction inside the city was felt subjectively, there has thus far been no objective and quantitative study of its variation to reflect the intracity population flows and their corresponding relationship with lockdown policy stringency from the view of remote sensing (RS) images with the high resolution under 1 m. Accordingly, we here provide a quantitative investigation of the traffic density reduction before and after lockdown was implemented in six cities (Wuhan, Milan, Madrid, Paris, New York, and London) around the world heavily affected by the COVID-19 epidemic, which is accomplished by extracting vehicles from the multitemporal high-resolution RS images. A novel vehicle detection model combining unsupervised vehicle candidate extraction and deep learning identification was specifically proposed for the images with the resolution of 0.5 m. Our results indicate that traffic densities were reduced by an average of approximately 50% (and as much as 75.96%) in these six cities following lockdown. The influences on traffic density reduction rates are also highly correlated with policy stringency, with an  $R^2$  value exceeding 0.83. Even within a specific city, the traffic density changes differed and tended to be distributed in accordance with the city's land-use patterns. Considering that public transport was mostly reduced or even forbidden, our results indicate that

Manuscript received January 10, 2021; revised April 14, 2021; accepted April 21, 2021. Date of publication May 10, 2021; date of current version June 11, 2021. This work was supported in part by the National Natural Science Foundation of China under Grant 61971317, Grant, 61822113, and in part by the Natural Science Foundation of Hubei Province under Grant 2020CFB594 and Grant 2018CFA050, in part by the National Key Research and Development Program of China under Grant 2018YFA0605500, and in part by the Science and Technology Major Project of Hubei Province (Next-Generation AI Technologies) under Grant 2019AEA170. (*Corresponding authors: Bo Du; Liangpei Zhang.*)

Chen Wu, Sihan Zhu, Jiaqi Yang, Meiqi Hu, Liangpei Zhang, and Chengxi Han are with the State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan 430072, China (e-mail: chen.wu@whu.edu.cn; zhusihan96@whu.edu.cn; jiaqiy@whu.edu.cn; meiqi.hu@whu.edu.cn; zlp62@whu.edu.cn; chengxihan@whu.edu.cn).

Bo Du is with the National Engineering Research Center for Multimedia Software, Institute of Artificial Intelligence, School of Computer Science and Hubei Key Laboratory of Multimedia and Network Communication Engineering, Wuhan University, Wuhan 430072, China (e-mail: gunspace@163.com).

Lefei Zhang and Meng Lan are with the School of Computer Science, Wuhan University, Wuhan 430072, China (e-mail: zhanglefei@whu.edu.cn; menglan@whu.edu.cn).

Digital Object Identifier 10.1109/JSTARS.2021.3078611

city lockdown policies are effective at limiting human transmission within cities.

*Index Terms*—City lockdown, COVID-19, high-resolution, remote sensing (RS), traffic density.

#### I. INTRODUCTION

N 2020, the spread of the novel coronavirus (COVID-19) completely changed human life across the whole world [1], [2]. In order to control the COVID-19 epidemic, the city of Wuhan firstly implemented a stringent lockdown policy [3], [4], which appears to be the largest quarantine to date and was unprecedented in human public health history [5], [6]. As the global COVID-19 epidemic worsened, many other cities around the world subsequently implemented similar lockdown policies, including limiting public transport, closing schools and non-essential shops, ordering residents to stay and work at home, prohibiting public events and gatherings, etc., to control transmission [7]–[14]. Numerous studies have also indicated that such control measures can mitigate the growth of the COVID-19 epidemic [6], [15]–[20].–

Since the details of lockdown policies and their degrees of stringency have varied across different cities [21], [22], it is difficult to quantitatively evaluate their effects and draw fair global comparisons. Some researches used mobile locations or social media data to study human mobility [23]–[26]. Traffic density is another good indicator of intracity population flow, as reductions in this metric have certainly been felt by the inhabitants of the cities under lockdown. However, it is difficult to obtain accurate and quantitative traffic data from various cities in different countries.

High-resolution remote sensing (RS) data can provide objective and consistent observations among different cities and between two periods (before and after city lockdown) [27]–[34], which offers a unique opportunity to evaluate the traffic density reduction caused by city lockdowns during the COVID-19 epidemic for a fair comparison [35]–[37]. Although a recent work addressed an analysis of traffic pattern during COVID-19 epidemic, it used the images with the resolution of 3 m, which

This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 License. For more information, see https://creativecommons.org/licenses/by-nc-nd/4.0/

#### TABLE I

METADATA OF THE COLLECTED HIGH-RESOLUTION RS IMAGES COVERING THE HEAVILY AFFECTED CITIES OF EARLY COVID-19 EPIDEMIC, INCLUDING WUHAN, MILAN, MADRID, PARIS, LONDON, AND NEW YORK. THESE IMAGES WERE ALL ACQUIRED BOTH BEFORE AND AFTER CITY LOCKDOWN WITH THE SMALLEST INTERVALS POSSIBLE. SOME IMAGES ARE MOSAICS OF TWO OR THREE IMAGES, WITH THEIR ACQUISITION DATA AND TIME SHOWN IN THE BRACKET

City	Lockdown Date	Image Date	Image Time (Local)	Day of the Week	Image Area (km <sup>2</sup> )	Resolution (m)
Wuhan	2020/1/23 *1	2019/10/17	11:26:26	Thursday	171.0	0.50
		2020/2/4	11:09:42.1 (+10s)	Tuesday	_	0.58
Milan	2020/3/8 *2	2019/10/16	11:33:57.3	Wednesday	32.6	0.51
		2020/3/28	11:22:47.0	Saturday		0.58
Madrid	2020/3/14 *3	2019/7/18	12:17:06.8 (+18.7s)	Thursday	65.8	0.50
		2020/4/3	12:16:33.8	Friday	_	0.50
Paris	2020/3/17 *4	2020/1/18	11:59:30.5	Saturday	89.0	0.53
		2020/3/28	12:10:46.3	Saturday	_	0.64
New York	2020/3/22 *5	2020/2/19	11:01:03.1 (+23.5s)	Wednesday	70.0	0.52
		2020/4/6	10:49:46.1 (+30.4s/+50.9s)	Monday	_	0.53
London	2020/3/23 *6	2019/5/14	11:14:19.5	Tuesday	46.6	0.62
		2020/4/21	11:09:17.5 (+15m 24.1s)	Monday/ Wednesday		0.54
		2020/4/23				

<sup>+1</sup>Wuhan municipal headquarters for the COVID-19 epidemic prevention and control, 2020, Announcement No. 1. http://www.gov.cn/xinwen/2020-01/23/content\_5471751.htm.

\*<sup>2</sup>Presidenza del Consiglio dei Ministri, 2020, Coronavirus, le misure adottate dal Governo. http://www.governo.it/it/coronavirus-misure-del-governo

\*3El País, 2020, Lack of testing hampering Spain's efforts to slow coronavirus outbreak. https://english.elpais.com/society/2020-03-18/lack-of-testing-hampering-spainsefforts-to-slow-coronavirus-outbreak.html.

\*<sup>4</sup>The Independent, 2020, Coronavirus: France imposes 15-day lockdown and mobilises 100 000 police to enforce restrictions. https://www.independent.co.uk/news/world/ europe/coronavirus-france-lockdown-cases-update-covid-19-macron-a9405136.html.

\*5 New York State, 2020, Governor Cuomo Signs the 'New York State on PAUSE' Executive Order. https://www.governor.ny.gov/news/governor-cuomo-signs-new-york-statepause-executive-order.

\*6. Prime Minister's Office 10 Downing Street, and The Rt Hon Boris Johnson MP, 2020, Prime Minister's statement on coronavirus (COVID-19): 23 March 2020 https: //www.gov.uk/government/speeches/pm-address-to-the-nation-on-coronavirus-23-march-2020.

is hard to identify normal vehicles accurately with such a resolution [38]. For most existing studies about vehicle detection on RS imagery, they are based on the aerial images with limited experimental areas, since their resolutions are smaller than 0.3m and have enough spatial details [39]–[46]. The problem is, only a few satellite sensors can reach the resolution of 0.3 m, and they are not just in the right pathway to acquire the necessary images for studying city lockdown. Hence, it is also necessary to develop a robust vehicle extraction model for RS images with a lower and more common resolution, which can be employed in the complex scenes of practical applications covering the whole city.

In the article, we use the number of vehicles extracted from multitemporal high-resolution RS images before and after lockdown in six cities around the world, with the goal of conducting an objective and quantitative study of traffic density reduction caused by city lockdown during the COVID-19 epidemic. A novel vehicle detection model that combines a morphology filter and multibranch deep learning identification network was developed to quantify the impact of city lockdown on traffic density. We further aim to analyze the correlation between traffic density reduction and lockdown stringency, as well as to provide an interpretation of the geographic view within the cities.

We choose six large and famous cities for analysis: Wuhan, Milan, Madrid, Paris, New York, and London, all of which were heavily affected in the early COVID-19 epidemic [47] and subsequently implemented stringent lockdown measures [4], [7], [9], [10], [13], [14]. Multitemporal RS images with resolution of 0.5 m covering the core areas of these cities, acquired before and after the implementation of city lockdown policy, were collected for a total study area of 475 km<sup>2</sup> at one time. Open street map (OSM) was used to extract road regions [48], while a COVID stringency index [21], [22] was utilized to evaluate the city lockdown policy.

References for a total area of 63 km<sup>2</sup> and 35 770 labeled vehicles indicated that our vehicle detection results obtain a total accuracy of 69.63%, which is satisfactory at this resolution in practical applications. Following analysis of the vehicle density changes, our results indicate that the traffic densities reduced by an average of approximately 50% in these six cities after city lockdown, with a decline sometimes as high as 75.96%. The influence on traffic density reduction rates is highly correlated with policy stringency, with an  $R^2$  exceeding 0.83. In terms of the view inside the city, traffic density changes also varied according to city land-use patterns. Considering that public transport was either limited or forbidden during these periods [4], [49]–[51], city lockdown policy can be deemed effective in controlling intracity human transmission.

## II. STUDY SITE AND RS IMAGES

In order to objectively compare the traffic density variations before and after lockdown in the six large cities selected, we collected multitemporal high-resolution RS images to extract the numbers of vehicles on the road. The metadata of all RS images used in this article is given in Table I. Almost all RS images were acquired by the Pleiades satellite, with a resolution of nearly 0.5 m and four spectral bands (Blue, Green, Red, and near-Infrared). The only exception is the RS image covering Wuhan before lockdown. The nearest available and clear Pleiades image covering the study area with low cloud coverage was acquired in 2016, which is too long ago compared with the other image pairs. Accordingly, we selected the RS images from WorldView-3 instead, then resampled them to a resolution of 0.5 m and four spectral bands.

The city lockdown dates and subsequent RS image acquisition time are presented alongside the cumulative confirmed cases [52]–[57] and COVID-19 government response stringency index developed by Oxford University [21], [22] in Fig. 1. It can be observed that the RS images were all acquired in the rising phases of the COVID-19 epidemic when the governments were implementing the most stringent lockdown measures. These collected RS data will therefore be effective for evaluating the influence of lockdown policy on traffic density.

Since these six cities differ markedly in terms of size and area, we only selected their core regions with obvious landmarks.

- 1) For the city of Wuhan, the study area covers the region inside the second ring road.
- 2) For the city of Milan, the study area was bounded by SS11 road.
- 3) For the city of Madrid, we selected the region contained by the M-30 road as the study site.
- 4) For the city of Paris, the study area contains all arrondissements except for two parks.
- 5) For New York City, the study area covers the borough of Manhattan.
- 6) For the city of London, we selected the region covered by zone 1.

The article areas and multi-temporal high-resolution RS images are presented in Fig. 1. The total observation area at one time is  $475 \text{ km}^2$ .

In order to identify vehicles on the roads only, we selected OSM data for the six cities. The OSM data for "motorway," "trunk," "primary," and their corresponding "link" were classified as arterial roads with a buffer of 20 m, while those for "secondary," "tertiary," "unclassified," and their corresponding "link" were classified as collector roads with a buffer of 20 m; moreover, those for "residential" and "living\_street" were classified as local roads with a buffer of 15 m [58]. Only the vehicles within these buffers were extracted and counted. The OSM data are presented in Fig. 1. All of these images were processed using the GS pan-sharpening method and co-registered to the OSM maps to facilitate better alignment.

#### III. METHODOLOGY

SINCE the high-resolution RS imagery with the resolution of 0.5 m does not have enough shape features for extracting vehicles from the road, we proposed a novel vehicle extraction method combining morphology filter and deep learning model. The whole flowchart of the proposed method is shown in Fig. 3. In the first step of vehicle candidate extraction, OSM data with buffers were used to extract road surfaces; morphology filter was utilized to highlight bright and dark objects contrast to the road; the connected objects were selected by shape filter with a reasonable shape, aspect ratio, and filling proportion; finally, anchors centering the vehicle candidates were generated. In the second step, a multibranch deep learning model was trained and used to identify real vehicles. In the last step, post-processing with nonmaximum suppression was implemented to filter the remaining anchors, to obtain the final vehicle extraction results.

#### A. Vehicle Candidate Extraction

Since the vehicles identified in the RS images with resolution of 0.5 m cannot provide enough shape information to facilitate direct detection, we decide to combine unsupervised vehicle candidate extraction with deep learning identification in our model. The goal of the unsupervised vehicle candidate extraction is to find possible vehicle targets and remove interference on the road, while the deep learning identification is used to distinguish between vehicles and nonvehicles.

During the process of vehicle candidate extraction, the basic concept is that vehicles in RS images contrast with the road background, enabling them to be captured by human interpreters. Accordingly, we first separate the bright and dark objects by segmenting the contrast density images using the TopHat and BottomHat morphology process [59]; subsequently, the connected objects are filtered according to their areas, shapes, and compactness, as shown in Fig. 4. In more detail, the procedure is as follows.

In this process, only the road regions masked by OSM data are considered.  $7 \times 7$  TopHat and BottomHat morphology processes are utilized for each spectral band of the RS image to highlight bright and dark objects against the road background. Two contrast density images are generated by the Euclidean distance of the multiband morphology results, after which two binary images are obtained by separately thresholding TopHat and BottomHat density images in accordance with visual interpretation. The corresponding opening binary images are produced by means of a  $3 \times 3$  opening morphology process on the binary TopHat and BottomHat images and used as auxiliary information. Here, the opening process is used to avoid misdetection caused by the connection of multiple objects. Moreover, a vegetation mask is generated using the manual thresholding of the NDVI feature image to avoid false detection of tree shadows. We now have five types of input data: binary TopHat image; binary BottomHat image; binary Opening TopHat image; binary Opening BottomHat image; and NDVI mask.

In the first step, bright and dark objects are extracted separately by connecting the binary TopHat image and binary BottomHat image with the vegetation mask.

For dark objects, shadows always accompany bright vehicles and can thus easily be falsely detected as dark vehicles. Thus, dark objects are taken out by means of shadow removal if a certain proportion (e.g., 30%) of the contours of a dark object are adjacent to bright objects by one or two pixels. Notably, dark objects with fairly good vehicle shapes are retained.

In the next step, bright objects and dark objects are filtered according to their areas, shapes and compactness. There are three criteria: the area of objects should be neither too large or too small; the height and width of the minimum bounding rectangle should be smaller than the thresholds, while the aspect ratio should also not be too large; and the proportions of an object occupying its contour hull or minimum bounding box should be larger than a given threshold. Moreover, objects filtered by the third criterion may be falsely removed due to the connection of two nearby vehicles in the image with such a resolution. Therefore, for these removed objects, their corresponding objects in the binary opening image will be added instead, provided that the alternative opening objects satisfy the stricter criterion discussed above.

Finally, the bright objects and dark objects are combined to make up the vehicle candidates. However, since the pixels in



Fig. 1. RS images acquired before and after city lockdown. The images shown in each line represent Wuhan, Milan, Madrid, Paris, New York, and London, respectively. The first column presents the images before city lockdown, while the second column shows the images after city lockdown. Moreover, the third column shows the road networks from OSM; here, yellow represents arterial roads, red represents collector roads and blue represents local roads.



Fig. 2. City lockdown and subsequent RS image acquisition date are shown corresponding to the cumulative confirmed cases and COVID stringency index.

these candidates may not be especially accurate, while some vehicles may be divided into two objects for a number of reasons (e.g., a dark sunroof), we generate anchors that center the vehicle candidates. The bounding boxes of vehicle candidates are expanded with a height zoom ratio of [1, 1.5, 2] and width zoom ratio of [1, 1.25, 1.5], after which the anchor ratios are rotated by 90°. Normally, for each vehicle candidates have an obtain 18 anchors; however, if the vehicle candidates have an obvious direction with a large aspect ratio, the anchor expansion will only be generated in this direction.

#### B. Deep Learning Identification

After the vehicle anchors are obtained, we develop a multibranch CNN model to identify and distinguish between vehicles and nonvehicles. Since vehicles on RS images with such a resolution do not contain detailed shape information, we fuse multi-scale patches with R, G, B, and NIR bands that center the anchors to be the input of the deep learning model. The first input is a window patch of size  $64 \times 64$ , which is clearly larger than the vehicle, to facilitate extracting the background information; the second input is a sub-window patch of size of  $32 \times 16$ , aligned with the direction of the anchor; moreover, the third input is the aligned anchor patch, which is resized to  $32 \times 16$  for convenience.

The multibranch deep learning model is shown in Fig. 5. The structure of this model derives from VGG-16 [60]; it contains convolution layers, max pooling layers, ROI pooling layers, and fully connected layers. ROI pooling layers are used here to guarantee a fixed size for the output vector in each branch. The final layer uses a sigmoid function to output the probability that the detected object is a vehicle. When training the deep learning model, we pretrain each branch separately by connecting the

TABLE II TRAINING SAMPLES FOR VEHICLES AND NONVEHICLES IN HIGH-RESOLUTION RS IMAGES

City	Image Date	Vehicle Samples	Non-Vehicle Samples
Wuhan	20191017	965	2985
	20200204	479	2969
Milan	20191016	700	2800
	20200328	700	2800
Madrid	20190718	758	2890
	20200403	913	3502
Paris	20200118	987	3263
	20200328	949	3335
New York	20200219	1076	2851
	20200406	1006	2910
London	20190514	700	2800
	20200421	700	2800
Total		9933	35905

features after ROI pooling to three new fully connected layers, as in the multibranch model. The three trained branches are then connected, as in Fig. 5, with new fully connected layers, then re-trained with the same training samples. Since we have extracted numerous vehicle candidates, it is much easier to label the training samples from the candidates rather than drawing boxes directly from the images. The number of training samples selected in each image is given in Table II. All training and testing samples are normalized with reference to the statistics of their source images. Random flipping (both vertically and horizontally) is adopted as a data augmentation method during the training process.

In the optimization procedure, binary cross-entropy is used as the loss function. Since a quantity imbalance exists between the vehicle and non-vehicle training samples, we use a simple weighting approach in the loss function, which assigns  $\frac{n_v + n_n}{2n_v}$ to vehicle samples and  $\frac{n_v+n_n}{2n_n}$  to nonvehicle samples; here,  $n_v$  and  $n_n$  are the sample amounts of vehicles and nonvehicles. This simple approach is able to balance the weights of vehicle and nonvehicle samples during the calculation of loss. The optimizations of each single branch and the multi-branch model are all implemented 100 times, and the Adam optimizer is applied [61]; the batch size is set to 200, and the shuffle process is also used. More specifically, we use a warmup learning rate scheduler strategy [62], where the start rate is  $1e^{-4}$ , the max rate is  $1e^{-3}$ , the min rate is  $1e^{-6}$ , the warmup epoch is 20, the sustaining epoch is 0, and the decaying parameter is 0.8. Only for the training of the first branch with window patch, the start rate and max rate are changed to be  $1e^{-5}$  and  $1e^{-4}$ .

In the testing procedure, the testing samples are determined to be vehicles if the output probability of the deep learning model exceeds 0.5.

#### C. Postprocessing

In the postprocessing phase, there are two steps: the first is nonmaximum suppression (NMS), while the second is the removal of vehicles under temporal shadow coverage.

Since numerous anchors have been generated that center the vehicle candidates, several of them will be retained after deep learning refining is complete. Therefore, we utilize NMS to



Vehicle Candidate Extraction

Fig. 3. Flowchart of the proposed vehicle extraction method.



Fig. 4. Flowchart of Vehicle Candidate Extraction.

choose the most probable detection box. Unlike the normal NMS, we apply some special processes here. First, if the heights, widths, and aspect ratios of the anchors do not satisfy the shape filter criterion, they will be suppressed. Second, in addition to the intersection over union, the intersection over area of the anchor with a maximum probability is also used to filter repetitive anchors. Third, if a suppressed anchor shows a probability that is only 0.05 less than the remaining one, but has the minimum area, it will be retained instead. After the NMS process is complete, the detection results for vehicles on the high-resolution RS images are obtained.

Since some of these images were acquired in winter, the solar altitudes are still low even when the acquisition time is midday. This phenomenon leads to more shadow coverage appearing in only one image of a multitemporal pair, which will result in unfair comparison of vehicle numbers on the road. We therefore utilize a Tasi's ratio image to find and extract shadow coverages [63]. Shadow areas are segmented by means of manual thresholding. A  $5 \times 5$  Closing morphology process and  $9 \times 9$  opening morphology process are subsequently implemented so that only large-area shadow regions remain. The union of shadow areas in a multi-temporal image pair is used to remove the covering vehicles in both images. All results and statistics presented in this article are based on the detection maps following multitemporal shadow coverage removal.

#### IV. EXPERIMENTS AND RESULTS

## A. Results and Accuracy Evaluation

The examples of vehicle detection results are shown in Fig. 6. It can be observed that after city lockdown, the vehicle densities in these images obviously reduced. Most vehicles in these images were successfully detected, and the vehicle numbers were accurately estimated.

In order to demonstrate the credibility of our method, we selected nine regions for each RS image (for a total of 108 reference regions) and manually labeled all vehicles. The total size of the reference area extends to  $63 \text{ km}^2$  with 35 770 labeled vehicles. Since the objective of this study is to count the number of vehicles, a detection will be judged to be true if the detection box covers the labeled box.

The total accuracy of the proposed model, comparison methods and the corresponding ablation experiments are given in Table III; here, "all image training" represents the proposed model. The comparison method selected is the well-known faster RCNN with rotating box. Since the training sample set for our proposed model is not suitable for faster RCNN, we attempt two ways of implementing this model. The first way involves downsampling the DOTA dataset to a resolution similar to that of our data, then training the faster RCNN model for vehicle



Fig. 5. Diagram of multibranch deep learning model.



Fig. 6. Vehicle detection results in multi-temporal high-resolution RS images, labeled with yellow boxes. (a) Zoomed-in images covering the road near Hankou Railway Station In Wuhan. (b) Zoomed-in images covering the Centrale FS in Milan. (c) Zoomed-in images covering the Puerta de Alcala in Madrid. (d) Zoomed-in images covering the Place de la Concorde in Paris. (e) Zoomed-in images covering the road near the United Nations headquarters in New York city. (f) Zoomed-in images covering the Westminster Bridge in London. The numbers in yellow rectangles indicates the number of vehicles detected in the image by our model.

detection [64]. In the second way, we conduct fine-tuning with the pretrained model, as in the first way, based on half of the references. As Table III indicates, the classical faster RCNN obtains far lower accuracies than the proposed model; this is because the spatial shape information is lacking in images with a resolution of 0.5m, which are unsuitable for direct object detection. As given in Table III, vehicle candidate extraction obtains a recall rate of 85.42%, meaning that it has found most vehicles in the image. The objective of deep learning identification is to increase the precision rate while simultaneously maintaining the recall rate. After DL refining is complete, it can be observed that the precision rate increases very substantially (11.66% to 69.86%), while the recall rate is kept relatively steady (85.42%)

	Precision R	ate Recall Ra	te F1 Score
Vehicle Candidate Extraction	11.66%	85.42%	20.32%
Single Image Training	64.80%	65.14%	64.60%
All Images Training with Single Image Fine-tune	75.77%	62.27%	68.08%
All Images Training without Weighting	68.83%	69.61%	68.99%
All Images Training without Anchor Generation	79.19%	57.60%	66.39%
All Images Training only for Anchor Branch	33.57%	80.06%	46.63%
All Images Training only for Sub-Window Branch	71.94%	64.71%	67.65%
All Images Training only for Window Branch	69.04%	64.69%	66.41%
All Images Training for Sub-Window + Anchor Branch	65.45%	70.12%	67.44%
All Images Training for Window + Anchor Branch	61.36%	72.93%	66.35%
All Images Training for Window + Sub-Window Branch	74.90%	63.23%	68.25%
Faster RCNN Trained with DOTA	30.36%	9.32%	10.36%
Faster RCNN Fine-tune with Reference	42.36%	6.68%	11.03%

 TABLE III

 TOTAL ACCURACY OF THE PROPOSED MODEL, COMPARISON METHODS, AND ABLATION EXPERIMENTS

TABLE IV

69.86%

69.90%

69.63%

STATISTICS OF VEHICLE NUMBERS IN THE SIX CITIES BEFORE AFTER LOCKDOWN, ALONG WITH THEIR CHANGE RATIOS

City	Acquisition Time	<b>Total Vehicle Number</b>	Vehicle Number on Arterial Road
Wuhan	Before Lockdown	59338	25736
	After Lockdown	24620	6186
	Change Ratio	<u>-58.51%</u>	<u>-75.96%</u>
Milan	Before Lockdown	35908	4316
	After Lockdown	20929	1596
	Change Ratio	<u>-41.71%</u>	<u>-63.02%</u>
Madrid	Before Lockdown	64581	18376
	After Lockdown	66327	9649
	Change Ratio	+2.70%	<u>-47.49%</u>
Paris	Before Lockdown	35449	16964
	After Lockdown	19326	6000
	<u>Change Ratio</u>	<u>-45.48%</u>	<u>-64.63%</u>
New York	Before Lockdown	33408	15358
	After Lockdown	38101	12632
	Change Ratio	+14.05%	<u>-17.75%</u>
London	Before Lockdown	33782	9231
	After Lockdown	37004	6585
	<u>Change Ratio</u>	<u>+9.54%</u>	<u>-28.66%</u>

to 69.90%). Single Image Training means that the DL model for each image is trained only with the training samples themselves. The accuracy results show that more training samples can yield more robust performance, where the best model is trained using all training samples. Moreover, we also test the result of the DL model that is trained with all samples and fine-tuned specific to the testing image. We find that the fine-tuned model identifies vehicles more accurately, but also misses more targets; this may be because the fine-tuning increases the model's identification ability, but will also falsely remove some vehicles if they are not covered in the training samples of the testing image.

All Images Training

The proposed weighting and anchor generation processes are also evaluated by ablation. The experiments show that anchor generation increases the total accuracy (F1 score) by 3%, while the weighting process increases the accuracy by less than 1%; since the imbalance between vehicle and non-vehicle samples is not severe, the weighting process improves the performance only slightly. Moreover, as the proposed model consists of three branches, we test various combinations of different branches. The ablation experiments reveal that the proposed method with all three branches outperforms those with only one or two branches. The detailed accuracies for the six cities are given in Table IV It can be observed from the table that almost all results have accuracies higher than 65%. These accuracies are all satisfactory in practical applications, especially considering the lack of detailed shape information, the complex acquisition environments, and the large covering areas.

#### B. Changes of Traffic Density

The vehicle number statistics before and after lockdown, along with their change ratios, are given in Table V. It can be observed that in the entire study area, the cities of Wuhan, Milan, and Paris exhibited obvious reductions, at the rate of approximately -50%, while the other three cities showed a slight increase.

It is worth noting that, in these cities, stopped vehicles may be parked along the roadside, meaning that it is difficult to distinguish between parked vehicles and running vehicles on the same road. Therefore, in order to better evaluate the real influence of city lockdown on traffic, we create statistics for vehicles on the arterial roads in each city, which are shown in the second column of Table V. As the table indicates, city lockdown

TABLE V Vehicle Detection Accuracy in All Images Covering Six Cities

City	Image Date	<b>Precision Rate</b>	<b>Recall Rate</b>	F1 Score
Wuhan	20191017	76.28%	66.85%	71.26%
	20200204	63.32%	65.91%	64.59%
Milan	20191016	70.20%	82.06%	75.67%
	20200328	74.90%	67.76%	71.15%
Madrid	20190718	84.61%	71.36%	77.42%
	20200403	74.52%	69.43%	71.89%
Paris	20200118	62.63%	65.91%	64.23%
	20200328	62.17%	55.85%	58.84%
New York	20200219	64.13%	75.46%	69.34%
	20200406	71.17%	65.51%	68.22%
London	20190514	66.44%	75.60%	70.72%
	20200421	67.90%	77.06%	72.19%
Total		69.86%	69.90%	69.63%

obviously decreases the vehicle densities in the main traffic routes of all six cities. Among these six cities, transportation in Wuhan was influenced by city lockdown to the greatest extent, i.e., by 75.96%. Considering that Wuhan completely forbid public transport within the city [4], this significant reduction of vehicle density proved that the stringent implementation of lockdown policy evidently limited human transmission. Paris and Milan show similar influences on traffic, with reductions of about 65%, while Madrid exhibits a comparatively lower reduction of 47.49% that still approximates to 50%. Finally, London's lockdown policy reduced the vehicle density by 28.66%, while New York City showed the least effect with a reduction of 17.75%.

# C. Traffic Density Change and COVID Stringency Index

It can be seen that the change ratios of vehicle numbers on the arterial roads of these six cities can be ranked as follows: Wuhan>Paris≈Milan>Madrid>London>New York (see Table IV). These rankings are quite similar to and in accordance with the countries' COVID stringency index [21] on the RS acquisition days [as shown in Fig.1(b)], with the city of Wuhan being the only outlier. According to the computation methodology of the COVID stringency index, the index value is determined by a subindex based on the lockdown policies and their implementation range [21]. Since the stringent Wuhan lockdown limited the spread of the COVID epidemic throughout the whole country of China [3], [6], [17], [65], all of the most stringent policies were implemented in the city of Wuhan, and China's overall COVID stringency index was decreased through the local implementation of stringent policy. A similar situation occurred for the stringency index of New York, which was analyzed separately in [21].

Accordingly, in order to evaluate the correlation between COVID stringency index and traffic density change ratio, we correct these indices to be city-wise, as shown in Fig. 7(a). The policy subindex values were retained and the flag for each subindex was assigned to be "general" in the city-wise index calculation, since all of these six cities were heavily affected by COVID-19 epidemic in the corresponding countries on those days (the index of New York was used directly, since it is the only city to have a separate index [21]). Using the corrected



Fig. 7. (a) COVID stringency indices for the countries as a whole and the specific cities. (b) Change ratios of vehicle numbers in the six cities and their arterial roads are regressed using the COVID stringency indices.

city-wise COVID stringency index, we conducted a regression analysis between the traffic density change ratios and the indices by means of quadratic polynomial fitting, as shown in Fig. 7(b). It can be observed from these results that the  $R^2$  values are both as high as 0.83, which indicates that the reduction in traffic density is highly correlated with the stringency of lockdown policy.

#### D. Distribution of Traffic Density Changes

The statistics of traffic density distribution is presented in Fig. 8. From the perspective of the cities' core regions, the traffic density colors become obviously dim in Wuhan, Milan, and Paris; this decline can also be proven with reference to the reduction of vehicle numbers for the whole city in Table IV. In the other three cities, some parts become brighter while others become darker, which can be explained by the fact that more vehicles were stopped in the residential regions.

Examining the traffic density changes, moreover, reveals that in all six cities, the arterial roads exhibit obvious vehicle reduction, since the deep blue mostly appears along the arterial roads. For the three cities that show increasing vehicle numbers in the entire cities (Madrid, New York, and London), the obvious decrease in vehicle numbers is mainly concentrated on the



Fig. 8. Statistics of vehicle numbers in  $300 \times 300$  m blocks in the six cities under analysis. The first column presents the vehicle distributions before lockdown, while the second indicates the vehicle distributions after lockdown. The third column shows the traffic density changes caused by lockdown. The left two columns are presented with equal interval slices, while the last column is shown with Jenks natural break slices for better illustration [66]. The color slices are shown under the traffic density maps; here, the densities in the first two columns of each line are sliced with the same range to facilitate comparison. The rows from top to bottom indicate the statistics for Wuhan, Milan, Madrid, Paris, New York, and London.

arterial roads, while increases may represent residential regions. For example, Uptown Manhattan in New York City shows a significant increase in vehicle density, which proves that more vehicles were stopped near their homes due to the stay-at-home order; moreover, the center of London's zone 1 shows vehicle density reduction, while its edges become brighter in the density slice, which may be because there are more apartments in the city center.

#### V. DISCUSSION AND CONCLUSION

Our results demonstrate that the lockdown policies during the COVID-19 epidemic clearly reduced traffic density by an average of 49.59%, and as much as 75.96%, by comparing the vehicle numbers before and after lockdown in six large cities (Wuhan, Milan, Madrid, Paris, New York, and London) that were the heavily affected in the early global COVID-19 outbreak. The influence on traffic density change ratios can be ranked in size order as follows: Wuhan> Paris≈Milan > Madrid> London>New York; these rankings exhibit extremely high correlations with the COVID lockdown policy stringencies (the  $R^2$  is higher than 0.83). We also find that traffic density reductions were spatially relevant to the land-use distribution within the cities.

In order to mitigate the COVID-19 outbreak, similar lockdown policies were implemented in many cities all over the world [4], [7]–[14], [67]. Studies have indicated that intercity travel bans can delay the progression of the epidemic to other cities by several days [6], [15], [17]. At the same time, control measures within cities, including stay-at-home orders, public transport limitations, closures of schools and workplaces, and bans on public gatherings, have been proven to be effective in decreasing the transmissibility and reducing the case incidence of COVID-19 [6], [18], [20], [68]. One key aspect of these lockdown measures within the city is the control of intracity population transmission [3]. At the moment, most corresponding studies are based on the policy interpretation [6], [15], [17], mathematical modeling [20], [68], and the intercity population flow data [6], [15], [17]; however, there has still been no research on quantitatively evaluating the intracity human transmission affected by city lockdown measures around the world with the traffic density changes. As we know, control measures during city lockdown will evidently affect the traffic situation [67]. Accordingly, by quantitatively analyzing the traffic density variations in six famous cities heavily affected in the early COVID-19 epidemic, we find that the traffic densities undergo a significant decrease after city lockdown, and are also strongly positively correlated with the stringency of control measures. Considering that public transport in these cities was largely limited and sometimes even forbidden [4], [49]–[51], this article indicates that stringent lockdown policy is effective in controlling human transmission. Our study provides new insight into these cities during the epidemic, and can thus help researchers and policy analysts better understand and develop epidemic containment measures to control COVID-19 outbreaks.

Our results may also help in the development of scientific recommendations for lockdown policy implementation. From

Fig. 7, we may infer that if the lockdown policy is not sufficiently stringent, its effect on controlling transmission will be slight. According to the regression, when the COVID-19 policy stringency is below 74, the numbers of vehicles on the arterial roads may not even reduce. After city lockdown, the traffic density reductions within the cities vary, which may reflect some potential land-use patterns for future city planning.

A recent work also addressed a study on the traffic pattern of cities under lockdown during the COVID-19 epidemic [38]. However, the RS images used in this article are acquired by Planet with the resolution of 3 m. For most normal vehicles in cities, they are smaller than  $5 \times 2$  m, which only occupy less than  $2 \times 1$  pixels in the image. Besides, this article utilized TopHat process to separate vehicles from the roads, which is only sensitive to bright vehicles. So, this previous work may not identify all the vehicles very accurately. It worth noting that this previous work also indicated the obvious reduction of traffic density, and its correlation with lockdown stringency, which shows another evidence for the conclusion of our study.

This article is also affected by the following limitations. In addition to the detection rate, it is difficult for the automatic vehicle detection algorithm to distinguish between running vehicles on the road and stopped vehicles parked at the roadside. To solve this problem, we also present the statistics of numbers of vehicles on arterial roads, whereas this phenomenon cannot be avoided. Considering that there may be more vehicles parked at the roadside after a city lockdown has been put in place, the traffic density reduction in our study may be underestimated. The second problem is that, for fair comparison, we use OSM data for six cities across the world to extract road regions and define arterial roads. However, OSM data is a free geographic data source that is provided by individuals [48], meaning that we cannot guarantee the accuracy of road type information; this may also affect the fairness when comparing variations in traffic density.

#### REFERENCES

- "COVID-19 Dashboard by Center for System Science Engineering," Johns Hopkins University, Baltimore, MD, USA, 2020, [Online]. Available: https://www.arcgis.com/apps/opsdashboard/index.html#/ bda7594740fd40299423467b48e9ecf6
- [2] E. Dong, H. Du, and L. Gardner, "An interactive web-based dashboard to track COVID-19 in real time," *Lancet Infectious Dis.*, vol. 20, no. 5, pp. 533–534, 2020.
- [3] S. Chen, J. Yang, W. Yang, C. Wang, and T. Bärnighausen, "COVID-19 control in china during mass population movements at new year," *Lancet*, vol. 395, no. 10226, pp. 764–766, 2020.
- [4] "Wuhan municipal headquarters for the COVID-19 epidemic prevention and control," 2020, [Online]. Available: http://www.gov.cn/xinwen/2020-01/23/content\_5471751.htm
- [5] "Wuhan lockdown 'unprecedented', shows commitment to contain virus: WHO representative China," Reuters, London, U.K., 2020, [Online]. Available: https://www.reuters.com/article/us-china-healthwho-idUSKBN1ZM1G9
- [6] H. Tian *et al.*, "An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China," *Science*, vol. 368, no. 6491, pp. 638–642, 2020.
- [7] "Coronavirus: France imposes 15-day lockdown and mobilises 100,000 police to enforce restrictions," The Independent, London, U.K., 2020 Available: [Online]. Available: https://www.independent.co.uk/news/ world/europe/coronavirus-france-lockdown-cases-update-covid-19macron-a9405136.html

- [8] "Coronavirus: SMS messages. Alerting people across U.K. about latest coronavirus measures," Prime Minister's Office 10 Downing Street, London, U.K., 2020,[ Online]. Available: https://www.gov.uk/government/ news/coronavirus-sms-messages
- "Coronavirus, le misure adottate dal Governo," Presidenza del Consiglio dei Ministri, Rome, Italy, 2020, [Online]. Available: http://www.governo. it/it/coronavirus-misure-del-governo
- [10] N. Y. State, "Governor Cuomo signs the 'New York, NY, USA State On PAUSE' executive order," 2020, [Online]. Available: https://www.governor.ny.gov/news/governor-cuomo-signs-new-yorkstate-pause-executive-order
- [11] "Governor Cuomo issues guide essential services under 'New York, NY, USA State PAUSE' Executive Order," 2020, [Online]. Available: https://www.governor.ny.gov/news/governor-cuomo-issues-guidanceessential-services-under-new-york-state-pause-executive-order
- [12] "New york state on PAUSE," 2020.
- [13] E. País, "Lack testing hampering Spain's efforts to slow coronavirus outbreak," 2020, [Online]. Available: https://english.elpais.com/ society/2020-03-18/lack-of-testing-hampering-spains-efforts-to-slowcoronavirus-outbreak.html
- [14] Prime Minister's Office 10 downing street and The Rt Hon Boris Johnson MP, "Prime Minister's statement coronavirus (COVID-19): 23 March 2020," 2020, [Online]. Available: https://www.gov.uk/government/ speeches/pm-address-to-the-nation-on-coronavirus-23-March-2020.
- [15] M. Chinazzi *et al.*, "The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak," *Science*, vol. 368, pp. 395–400, 2020.
- [16] J. S. Jia, X. Lu, Y. Yuan, G. Xu, J. Jia, and N. A. Christakis, "Population flow drives spatio-temporal distribution of COVID-19 in China," *Nature*, vol. 582, pp. 389–394, 2020.
- [17] U. G. Moritz et al., "The effect of human mobility and control measures on the COVID-19 epidemic in China," Science, vol. 368, pp. 493-497, 2020.
- [18] K. Leung, J. T. Wu, D. Liu, and G. M. Leung, "First-wave COVID-19 transmissibility and severity in china outside Hubei after control measures, and second-wave scenario planning: A modelling impact assessment," *Lancet*, vol. 395, no. 10233, pp. 1382–1393, 2020.
- [19] B. F. Maier and D. Brockmann, "Effective containment explains subexponential growth in recent confirmed COVID-19 cases in China," *Science*, vol. 368, no. 6492, pp. 742–746, 2020.
- [20] K. Prem *et al.*, "The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: A modelling study," *Lancet Public Health*, vol. 5, no. 5, pp. e261–e270, 2020.
- [21] T. Hale *et al.*, "Oxford COVID-19 government response tracker," Blavatnik School Government, Univ. of Oxford, Oxford, U.K., 2020.
- [22] T. Hale *et al.*, "A global panel database of pandemic policies (Oxford COVID-19 government response tracker)," *Nature Hum. Behav.*, vol. 5, pp. 529–538, 2021.
- [23] X. Huang, Z. Li, Y. Jiang, X. Li, and D. Porter, "Twitter reveals human mobility dynamics during the COVID-19 pandemic," *PloS one*, vol. 15, no. 11, , 2020, Art. no. e0241957.
- [24] C. Xiong, S. Hu, M. Yang, W. Luo, and L. Zhang, "Mobile device data reveal the dynamics in a positive relationship between human mobility and COVID-19 infections," *Proc. Nat. Acad. Sci.*, vol. 117, no. 44, pp. 27087–27089, 2020.
- [25] S. Gao et al., "Association of mobile phone location data indications of travel and Stay-at-Home mandates with COVID-19 infection rates in the US," JAMA Netw. Open, vol. 3, no. 9, 2020, Art. no. e2020485.
- [26] Y. Kang, S. Gao, Y. Liang, M. Li, J. Rao, and J. Kruse, "Multiscale dynamic human mobility flow dataset in the U.S. during the COVID-19 epidemic," *Sci. Data*, vol. 7, no. 1, p. 390, 2020.
- [27] M. Reichstein, G. Camps-Valls, B. Stevens, M. Jung, J. Denzler, N. Carvalhais, and Prabhat, "Deep learning and process understanding for data-driven earth system science," *Nature*, vol. 566, no. 7743, pp. 195–204, 2019.
- [28] R. Anniballe *et al.*, "Earthquake damage mapping: An overall assessment of ground surveys and VHR image change detection after L'Aquila 2009 earthquake," *Remote Sens. Environ.*, vol. 210, pp. 166–178, 2018.
- [29] L. Moya *et al.*, "Detecting urban changes using phase correlation and *l*1-based sparse model for early disaster response: A case study of the 2018 sulawesi Indonesia earthquake-Tsunami," *Remote Sens. Environ.*, vol. 242, 2020, Art. no. 111743.
- [30] X. Zhang, P. Xiao, X. Feng, and M. Yuan, "Separate segmentation of multitemporal high-resolution remote sensing images for object-based change detection in urban area," *Remote Sens. Environ.*, vol. 201, pp. 243–255, 2017.

- [31] S. Liu, D. Marinelli, L. Bruzzone, and F. Bovolo, "A review of change detection in multitemporal hyperspectral images: Current techniques, applications, and challenges," *IEEE Geosci. Remote Sens. Mag.*, vol. 7, no. 2, pp. 140–158, Jun. 2019.
- [32] X. Xu, W. Li, Q. Ran, Q. Du, L. Gao, and B. Zhang, "Multisource remote sensing data classification based on convolutional neural network," *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 2, pp. 937–949, Feb. 2018.
- [33] Z. Xue, J. Li, L. Cheng, and P. Du, "Spectral–Spatial classification of hyperspectral data via morphological component analysis-based image separation," *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 1, pp. 70–84, Jan. 2015.
- [34] H. Su, Y. Yu, Q. Du, and P. Du, "Ensemble learning for hyperspectral image classification using tangent collaborative representation," *IEEE Trans. Geosci. Remote Sens.*, vol. 58, no. 6, pp. 3778–3790, Jun. 2020.
- [35] L. Eikvil, L. Aurdal, and H. Koren, "Classification-based vehicle detection in high-resolution satellite images," *ISPRS J. Photogramm. Remote Sens.*, vol. 64, no. 1, pp. 65–72, 2009.
- [36] H. Tanveer, T. Balz, F. Cigna, and D. Tapete, "Monitoring 2011–2020 traffic patterns in Wuhan (China) with COSMO-SkyMed SAR, amidst the 7th CISM military world games and COVID-19 outbreak," *Remote Sens.*, vol. 12, no. 10, 2020, Art. no. 1636.
- [37] X. Liu *et al.*, "High-resolution multi-temporal mapping of global urban land using landsat images based on the Google Earth Engine platform," *Remote Sens. Environ.*, vol. 209, pp. 227–239, 2018.
- [38] Y. Chen, R. Qin, G. Zhang, and H. Albanwan, "Spatial temporal analysis of traffic patterns during the COVID-19 epidemic by vehicle detection using planet remote-sensing satellite images," *Remote Sens.*, vol. 13, no. 2, p. 208, 2021.
- [39] H. Ji, Z. Gao, T. Mei, and B. Ramesh, "Vehicle detection in remote sensing images leveraging on simultaneous super-resolution," *IEEE Geosci. Remote Sens. Lett.*, vol. 17, no. 4, pp. 676–680, Apr. 2020.
- [40] J. Leitloff, S. Hinz, and U. Stilla, "Vehicle detection in very high resolution satellite images of city areas," *IEEE Trans. Geosci. Remote Sens.*, vol. 48, no. 7, pp. 2795–2806, Jul. 2010.
- [41] C. Tao, L. Mi, Y. Li, J. Qi, Y. Xiao, and J. Zhang, "Scene context-driven vehicle detection in high-resolution aerial images," *IEEE Trans. Geosci. Remote Sens.*, vol. 57, no. 10, pp. 7339–7351, Oct. 2019.
- [42] Z. Chen *et al.*, "Vehicle detection in high-resolution aerial images via sparse representation and superpixels," *IEEE Trans. Geosci. Remote Sens.*, vol. 54, no. 1, pp. 103–116, Jan. 2016.
- [43] T. Tang, S. Zhou, Z. Deng, L. Lei, and H. Zou, "Arbitrary-Oriented vehicle detection in aerial imagery with single convolutional neural networks," *Remote Sens.*, vol. 9, no. 11, p. 1170, 2017.
- [44] N. Audebert, B. L. Saux, and S. Lefevre, "Segment-before-Detect: Vehicle detection and classification through semantic segmentation of aerial images," *Remote Sens.*, vol. 9, no. 4, p. 368, 2017.
- [45] T. Tang, S. Zhou, Z. Deng, H. Zou, and L. Lei, "Vehicle detection in aerial images based on region convolutional neural networks and hard negative example mining," *Sensors*, vol. 17, no. 2, p. 336, 2017.
- [46] Q. Li, L. Mou, Q. Xu, Y. Zhang, and X. X. Zhu, "R3-Net: A deep network for multioriented vehicle detection in aerial images and videos," *IEEE Trans. Geosci. Remote Sens.*, vol. 57, no. 7, pp. 5028–5042, 2019.
- [47] Center for Systems Science and Engineering at Johns Hopkins University, "COVID-19 dashboard," 2020, [Online]. Available: https://coronavirus. jhu.edu/map.html
- [48] OpenStreetMap Foundation, "Open street map," 2020, [Online]. Available: https://www.openstreetmap.org
- [49] Connexion, "Covid-19 France: Transport gradually reduced," 2020, [Online]. Available: https://www.connexionfrance.com/Frenchnews/Covid-19-in-France-Transport-trains-buses-planes-SNCFgradually-reduced-says-transport-minister
- [50] "MTA slashes service, NJ transit limits ridership to essential personnel only," NBC New York, New York, NY, USA, 2020, [Online]. Available: https://www.nbcnewyork.com/news/local/mta-suspends-some-lines-ofservice-amid-coronavirus-staff-shortages/2341550/
- [51] Wikipedia, "Impact COVID-19 pandemic public transport," 2020, [Online]. Available: https://en.wikipedia.org/wiki/Impact\_of\_the\_COVID-19\_pandemic\_on\_public\_transport
- [52] RTVE, "The map of the coronavirus in Spain (in Spanish)," 2020, [Online]. Available: https://www.rtve.es/noticias/20201018/mapa-delcoronavirus-espana/2004681.shtml
- [53] U.K. Government, "Coronavirus (COVID-19) U.K.," 2020, [Online]. Available: https://coronavirus.data.gov.uk/#category=nations&map=rate
- [54] D. X. Yuan, "COVID-19/2019-nCoV time ser. infection data warehouse," 2020, [Online]. Available: https://github.com/BlankerL/DXY-COVID-19-Data

- [55] Emergenza Coronavirus, "Coronavirus emergency: the national response (in Italian)," 2020, [Online]. Available: http://www.protezionecivile.it/ attivita-rischi/rischio-sanitario/emergenze/coronavirus
- [56] New York, NY, USAC Health. COVID-19: Data, 2020, [Online]. Available: https://www1.nyc.gov/site/doh/covid/covid-19-data-archive.page
- [57] Gouvernement.fr. "COVID-19 France," 2020, [Online]. Available: https: //www.gouvernement.fr/info-coronavirus/carte-et-donnees
- [58] OpenStreetMap Wiki. Key: Highway, 2020, [Online]. Available: https: //wiki.openstreetmap.org/wiki/Key:highway
- [59] Z. Zheng et al., "A novel vehicle detection method with high resolution highway aerial image," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 6, no. 6, pp. 2338–2343, Dec. 2013.
- [60] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 2015, arXiv:1409.1556.
- [61] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2017, arXiv:1412.6980.
- [62] A. Gotmare, N. Shirish Keskar, C. Xiong, and R. Socher, "A closer look at deep learning heuristics: Learning rate restarts, warmup and distillation," in *Proc. Int. Conf. Learn. Representations*, 2019.
- [63] V. J. D. Tsai, "A comparative study on shadow compensation of color aerial images in invariant color models," *IEEE Trans. Geosci. Remote Sens.*, vol. 44, no. 6, pp. 1661–1671, Jun. 2006.
- [64] G. Xia et al., "DOTA: A large-scale dataset for object detection in aerial images," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., 2018, pp. 3974–3983.
- [65] Z. Wu and J. M. McGoogan, "Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: Summary of a report of 72 314 cases from the Chinese center for disease control and prevention," *JAMA*, vol. 323, no. 13, pp. 1239–1242, 2020.
- [66] Wiki.GIS.com, "Jenks natural breaks classification," 2018, [Online]. Available: http://wiki.gis.com/wiki/index.php/Jenks\_Natural\_Breaks\_ Classification
- [67] Wikipedia, "COVID-19 pandemic lockdowns," 2020, [Online]. Available: https://en.wikipedia.org/wiki/COVID-19\_pandemic\_lockdowns
- [68] A. J. Kucharski *et al.*, "Early dynamics of transmission and control of COVID-19: A mathematical modelling study," *Lancet Infect. Dis.*, vol. 20, no. 5, pp. 553–558, 2020.



Jiaqi Yang (Student Member, IEEE) received the B.S. degree in geographic information science from Dalian Maritime University, Dalian, China, in 2019. She is currently working toward the M.S. degree at the State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote Sensing, Wuhan University, Wuhan China.

Her research interests include deep learning and remote sensing image processing.



Meiqi Hu received the B.S. degree in surveying and mapping engineering from the School of Geoscience and info-physics, Central South University, Changsha, China, in 2019. She is currently working toward the M.S. degree at the State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote sensing, Wuhan University, Wuhan, China.

Her research interests include deep learning and multitemporal remote sensing image change detection.



**Chen Wu** (Member, IEEE) received B.S. degree in surveying and mapping engineering from Southeast University, Nanjing, China, in 2010, and received the Ph.D. degree in photogrammetry and remote sensing from the State Key Lab of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China, in 2015.

He is currently an Associate Professor with the State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China. His research interests in-

clude multitemporal remote sensing image change detection and analysis in multispectral and hyperspectral images.



**Bo Du** (Senior Member, IEEE) received the Ph.D. degree in photogrammetry and remote sensing from the State Key Lab of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China in 2010.

He is currently a Professor with the School of Computer Science and Institute of Artificial Intelligence, Wuhan University. He is also the Director of and National Engineering Research Center for Multimedia Software Wuhan University, Wuhan, China. He has more than 80 research papers published in

the IEEE TRANSACTIONS ON IMAGE PROCESSING, IEEE TRANSACTIONS ON CYBERNETICS, IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE IN-TELLIGENCE, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, etc. A total 14 of them are ESI hot papers or highly cited papers. His major research interests include machine learning, computer vision, and image processing.

Dr. Du is currently an Associate Editor for Neural Networks, Pattern Recognition and Neurocomputing. He is also a Reviewer of 20 Science Citation Index (SCI) magazines including IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, IEEE TRANSACTIONS ON CYBERNETICS, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, IEEE TRANSACTIONS ON IMAGE PROCESSING, IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, and IEEE GEOSCIENCE AND REMOTE SENSING LETTERS. He was the recipient of the Highly Cited Researcher (2019\2020) by the Web of Science Group, IEEE Geoscience and Remote Sensing Society 2020 Transactions Prize Paper Award, the IJCAI (International Joint Conferences on Artificial Intelligence) Distinguished Paper Prize, IEEE Data Fusion Contest Champion, and IEEE Workshop on Hyperspectral Image and Signal Processing Best paper Award, in 2018. He regularly serves as senior PC member of International Joint Conference on Artificial Intelligence and Association for the Advancement of Artificial Intelligence. He was an Area Chair for Indian Council of Philosophical Research.



Sihan Zhu received the B.S. degree in geographic information science from China University of Petroleum (East China), Qingdao, China in 2019. He is currently working toward the M.S. degree in surveying and mapping engineering at the State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote Sensing, Wuhan University, Wuhan, China.

His research interests include remote sensing image processing, transfer learning, and deep learning.



Liangpei Zhang (Fellow, IEEE) received the B.S. degree in physics from Hunan Normal University, Changsha, China, in 1982, the M.S. degree in optics from the Xi'an Institute of Optics and Precision Mechanics, Chinese Academy of Sciences, Xi'an, China, in 1988, and the Ph.D. degree in photogrammetry and remote sensing from Wuhan University, Wuhan, China, in 1998.

He is a Chair Professor with the State Key Laboratory of Information Engineering in Surveying, Mapping, and remote sensing, Wuhan University. He was

a Principal Scientist for the China state key basic research project (2011–2016) appointed by the Ministry of National Science and Technology of China to lead the remote sensing program in China. He has authored or coauthored than 700 research papers and five books. He is the Institute for Scientific Information (ISI) highly cited author. He is the holder of 30 patents. His research interests include hyperspectral remote sensing, high-resolution remote sensing, image processing, and artificial intelligence.

Dr. Zhang is a Fellow the *Institution of Engineering and Technology* (IET). He was a recipient of the 2010 Best Paper Boeing Award, the 2013 Best Paper ERDAS Award from the American Society of Photogrammetry and Remote Sensing and 2016 Best Paper Theoretical Innovation Award from the International Society for Optics and Photonics. His research teams won the top three prizes of the IEEE GRSS 2014 Data Fusion Contest, and his students have been selected as the winners or finalists of the IEEE International Geoscience and Remote Sensing Symposium student paper contest in recent years. He is the Founding Chair of the IEEE Geoscience and Remote Sensing Society Wuhan Chapter. He is currently an Associate Editor or an Editor for the IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING.



Lefei Zhang (Senior Member, IEEE) received the B.S. and Ph.D. degrees from Wuhan University, Wuhan, China, in 2008 and 2013, respectively.

He is currently a Professor with the School of Computer Science, Wuhan University, Wuhan, China. He was a Big Data Institute Visitor with the Department of Statistical Science, University College London, London, U.K., in 2016, and a Hong Kong Scholar with the Department of Computing, The Hong Kong Polytechnic University, Hong Kong, in 2017. His research interests include pattern recognition, image

processing, and remote sensing.

Dr. Zhang is an Associate Editor for *Pattern Recognition* and IEEE GEO-SCIENCE AND REMOTE SENSING LETTERS.



**Chengxi Han** (Student Member, IEEE) received the B.S. degree from the School of Geosciences and Info-Physics, Central South University, Changsha, China, in 2018. He is currently working toward the Ph.D. degree in photogrammetry and remote sensing at the State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China.

His research interests include deep learning and remote sensing image processing.

Meng Lan (Student Member, IEEE) received the B.S. degree from the School of Computer Science in 2018 from Wuhan University, Wuhan, China, where he is currently working toward the Ph.D. degree. His research interests include deep learning and image processing.