

REVIEW ARTICLE



Urban land-use analysis using proximate sensing imagery: a survey

Zhinan Qiao and Xiaohui Yuan

University of North Texas, Denton, TX, USA

ABSTRACT

Urban regions are complicated functional systems that are closely associated with and reshaped by human activities. The propagation of online geographic information-sharing platforms and mobile devices equipped with the Global Positioning System (GPS) greatly proliferates proximate sensing images taken near or on the ground at a close distance to urban targets. Studies leveraging proximate sensing images have demonstrated great potential to address the need for local data in the urban land-use analysis. This paper reviews and summarizes the state-of-the-art methods and publicly available data sets from proximate sensing to support land-use analysis. We identify several research problems in the perspective of examples to support the training of models and means of integrating diverse data sets. Our discussions highlight the challenges, strategies, and opportunities faced by the existing methods using proximate sensing images in urban land-use studies.

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1. Introduction

Analysis of urban land-use enables researchers, practitioners, and administrators to understand city dynamics and to plan and respond to urban land-use needs. It also reveals human social activities in terms of locations and types in cities, which is closely related to human behaviors with respect to buildings, structures, and natural resources (Wang and Hofe 2008, Yuan and Sarma 2011). Applications such as urban planning, ecological management, and environment assessment (Säynäjoki *et al.* 2014) require the most updated knowledge of urban land-use. Conventionally, urban land-use information is obtained through field surveys, which is labor-intensive and time-consuming. The employment of proximate sensing data has demonstrated the potential of automatic, large-scale urban land-use analysis (Leung and Newsam 2009, Qiao *et al.* 2020) and thus attracted researchers from fields of computer science and geographic information systems (Qiao *et al.* 2021).

Proximate sensing images, which refer to images of close-by objects and scenes (Leung and Newsam 2009), complements the overhead imagery by providing information of objects from another perspective and brings completely disparate clues for urban land-use analysis. Urban land-use is closely related to human activities and demands more approximate means to investigate the cities (Lef'evre *et al.* 2017). The crucial features

associated with human activities are usually obscured from overhead imagery such as satellite images (Karasov *et al.* 2019). For example, differentiating commercial (e.g. office buildings) and residential buildings (e.g. apartments) is a typical problem in urban land-use analysis and the overhead imagery alone provides insufficient information for the aforementioned issue. Moreover, publicly available data that can be adopted as proximate sensing images are massive in volume. For example, over 300 million images are uploaded to Facebook every day (Dustin 2020), which enables the development of large-scale, data-driven approaches for urban land-use analysis.

This article is the first one that reviews the up-to-date studies on the employment of proximate sensing images for urban land-use analysis. The unique properties of proximate sensing images have motivated the development of novel methods, which necessitates a survey of data and methods to provide researchers a comprehensive review of the state-of-the-art. We categorize a diverse collection of emerging technological advancements on this topic and identify technical challenges, existing solutions, and research opportunities. Throughout the literature, we observe challenges in two aspects: a myriad of data sets and technical obstacles. Discussions are hence assembled on these challenges. Figure 1 illustrates the data sets and two associated issues: data cleaning and labeling. The AiRound, CV-BrCT, UCF Cross view, and Brooklyn and Queens data sets consist of ground-level and overhead images, and the rest contain only ground-level images. The majority of data cleaning methods use classifiers to filter out incompatible examples and for land-use labeling, information from OpenStreetMap (OSM) serves as the primary reference. Figure 2 shows the taxonomy of land-use analysis methods, which are grouped into three categories: building classification, ground imagery aggregation, and cross-view integration.

The remainder of this article is organized as follows. Section 2 summarizes the proximate sensing data for land-use analysis and presents the technical challenges in data cleaning and land-use example labeling. Section 3 reviews the state-of-the-art methods from the perspectives of building classification, data aggregation, and cross-view land-use classification. Section 4 presents a discussion and summarizes this paper with highlights of the opportunities for future research.

2. Proximate sensing data and preprocessing

2.1. Data sets

A vital source of proximate sensing images is the street view images provided by map service providers such as Google Street View, Apple Look Around, and Bing StreetSide. These services cover most major cities worldwide. In addition, companies such as Baidu, Tencent, Yandex, and Barikoi also provide regional street view images. Among these map service providers, GSV is the most influential geographical information service and was debuted in 2007. As of 2020, GSV has covered nearly 200 countries on four continents, which makes it an opportune data source for urban land-use analysis (Wikipedia 2020).

Another major source of proximate sensing images is the volunteer geographic information (VGI) platforms such as OpenStreetMap and social media services such as Instagram, Facebook, and Flickr. The affordability and portability of modern mobile devices rigged with cameras and GPS make every social media user a potential data

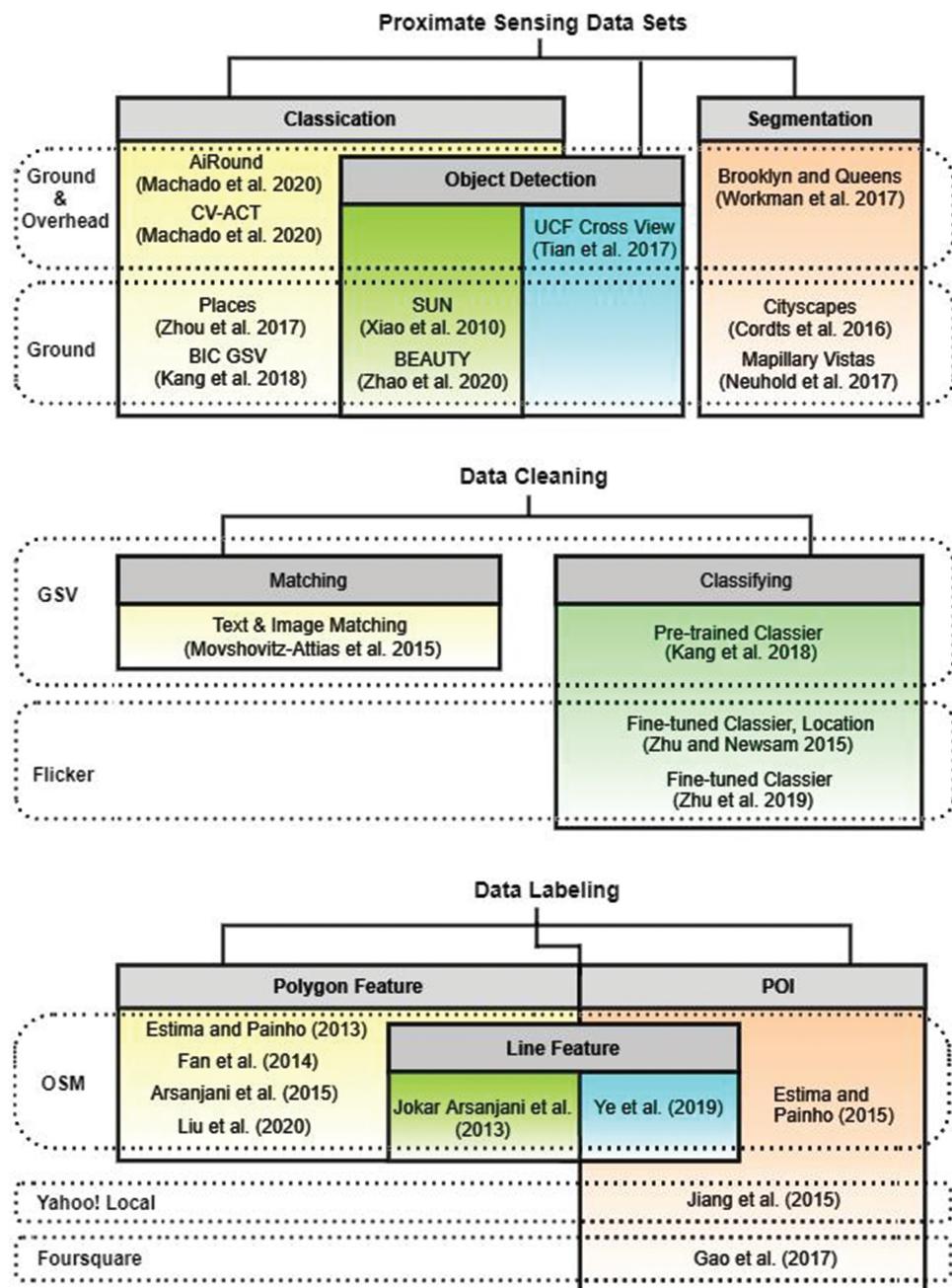


Figure 1. Proximate sensing data sets and associated issues.

provider (Terroso-Saenz et al. 2021). Consequentially, a large volume of images with GPS information has been created and continues to be updated every day. Such VGI data also contain annotations to assist urban land-use analysis (Muñoz et al. 2020, Mahabir et al. 2020a). Antoniou et al. (2016) reviewed VGI images for mapping land-use patterns and

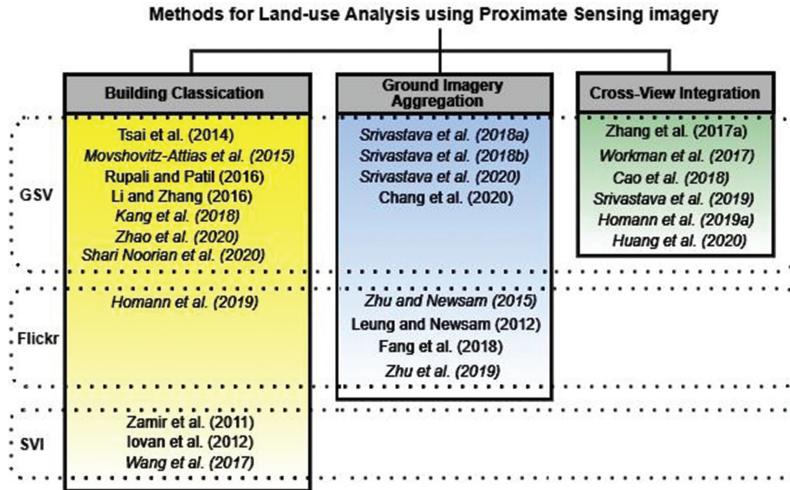


Figure 2. Taxonomy of land-use analysis methods. SVI denotes the unspecified street view images. The ones in italic are methods that employ deep learning.

found that more than half of the collected images are helpful to extract the land-use related information. An emerging form of volunteered street view images, e.g. Mapillary and OpenStreetCam, provides a rich source of spatial geotagged street-level images along roads. The coverage of the VGI images, however, varies greatly within and across cities (Mahabir *et al.* 2020b).

Table 1 summarizes the data sets adopted in the past studies. To our best knowledge, there is no widely adopted benchmark proximate sensing data set for urban land-use analysis. Some of these data sets, e.g. AiRound, CV-BrCT, UCF Cross view, and Brooklyn

Table 1. Proximate sensing data sets. Image types include overhead (O), ground (G), multi-spectral (M). Cityscapes consist of images in fine and coarse resolutions. For the data sets that have object detection examples, the corresponding entries denote the number of annotated objects.

Data Set	# of Images	# Class	Application
Places (Wang <i>et al.</i> 2017)	10,624,928	434	Classification
BIC GSV (Kang <i>et al.</i> 2018)	19,658	8	Classification
	1,165 (O)		
AiRound (Machado <i>et al.</i> 2020)	1,165 (G)	11	Classification
	1,165 (M)		
CV-BrCT (Machado <i>et al.</i> 2020)	24,000 (O) 24,000 (G)	9	Classification
SUN (Xiao <i>et al.</i> 2010)	131,072 313,884	908 4,479	Classification Obj. Detection
BEAUTY (Zhao <i>et al.</i> 2020)	19,070 38,857	4 8	Classification Obj. Detection
UCF Cross View (Tian <i>et al.</i> 2017)	40,000 (O) 15,000 (G)	–	Obj. Detection
Brooklyn and Queens (Workman <i>et al.</i> 2017)	53,649 (O) 177,930 (G)	206	Segmentation
Cityscapes (Cordts <i>et al.</i> 2016)	5,000 (fine) 20,000 (coarse)	30	Segmentation
Mapillary Vistas (Neuhold <i>et al.</i> 2017)	25,000	152	Segmentation

and Queens data sets, include both proximate sensing data and overhead imagery. Among these data sets, BIC GSV, AiRound, CV-BrCT, and Brooklyn and Queens data sets are designed specifically for the task of urban land-use classification. UCF Cross View data set has been used to align overhead and proximate images. Places and SUN data sets consist of a fairly large volume of data, part of which has been used for urban land-use classification by supplementing land-use annotations.

2.2. Data cleaning

A great challenge faced in the employment of the available data sets is image inconsistency, which necessitates data cleaning. Proximate sensing data vary greatly and the major issue is three-fold.

- (1) *Only a portion of the images captured from the ground perspective includes spatial, contextual information for urban land-use analysis.* The geo-tagged images available in online services such as Flickr and Facebook contain a large number of selfies, photographs of food, pets, and other contents that provide little help in understanding urban structures and land-use.
- (2) *There exists a disconnection between the contents of an image and its geographic coordinates.* Images are often captured views at a distance from the shooting point of the photographer. The geographic coordinates automatically embedded in these images reflect the location of the photo taker instead of the objects captured in the image. The images illustrate buildings or structures that are outside of the current land-use functional unit.
- (3) *Useful information of the image sets after removing irrelevant instances is limited for achieving high accuracy with satisfactory robustness.* Objects in images that provide hints of land-use may be insignificant due to the small size or off the center of the image. After all, these images are not taken intentionally for land-use classification, which makes data cleaning a crucial component in the process of land-use analysis.

Hence, the cleaning and refinement of proximate sensing images is a non-negligible problem.

To sift usable data from street view images, Movshovitz-Attias *et al.* (2015) constructed a database of manually identified business entities that are presented by location and textual information. The same description of unlabeled street view images was generated. The business entity was assigned to a street view image if the distance between the entity and the image is less than one street block. Images with irrelevant information or taken from a distance were discarded. Zhu and Newsam (2015) employed polygon outlines and classifiers to clean VGI data. Flickr images that are outside of the extracted polygonal regions are removed. A search strategy was used for data augmentation to ease the imbalance among classes of the training data.

An alternative means for data cleaning is applying pre-trained deep network models. Kang *et al.* (2018) adopted the VGG16 (Simonyan and Zisserman 2014) model fine-tuned on Places2 data set (Zhou *et al.* 2016). A large number of training examples in the Places2 data set and the overlapping of Places2 data and proximate sensing data make it a proper source to fine-tune the VGG16 model for land-use classification. The fine-tuned model

was used to decide if an image is relevant to urban land-use. Zhu *et al.* (2019) developed an online training method for data cleaning. To create a relatively large data set for fine-grained urban land-use classification, both Flickr and Google Images were used. The online adaptive training was implemented following the intuition that if the Softmax scores of an image are evenly distributed among all categories, this image is likely to be confusing and irrelevant to the land-use analysis. Images with strongly skewed prediction scores benefit the development of the model. Similar to negative mining (Yuan *et al.* 2002, You *et al.* 2015, Shrivastava *et al.* 2016), samples that result in a low probability value are discarded.

Table 2 summarizes the existing data cleaning methods. Most of the efforts are based on applying a classifier to identify suitable instances. Despite the effectiveness of removing loosely related instances, a gap between image contents and the land-use types still exists. The development of novel methods that automatically select the most representative images or preclude less informative ones is still of great importance to ensure successful land-use classification.

2.3. Land-use labeling

Proximate sensing requires labels for buildings and urban functional regions to support land-use analysis. The labels of land-use are often not readily available for the images, which poses a great challenge in research and deployment. OSM tags and the Point of Interest (POI) have been used in studies to derive land-use labels and annotate proximate sensing images (Vargas Muñoz *et al.* 2020). The OSM database consists of several sub-sets: points, places, roads, waterways, railways, buildings, land-use, and natural areas. OSM and map service providers such as Yahoo! Local (Jiang *et al.* 2015), Foursquare (Gao *et al.* 2017), Google Places, and ATTOM Data Solutions (2020) also provide geo-tagged POI data. However, the quality of OSM tags and POIs is usually undermined due to limited regularization and censorship. Hence, studies have been conducted to understand the usage of OSM tags and POIs.

An early effort of deriving labels from OSM data was conducted by Haklay and Weber (2008). The study found that the OSM tags are suitable for land-use analysis with an accuracy of 80% comparing to the existing survey data. Estima and Painho (2013) employed OSM tags for land-use classification and achieved an accuracy of 76%. Fan *et al.* (2014) asserted that OSM tags contain a vast amount of building information and the size and shape of building footprints also provide clues to the function of buildings. Arsanjani *et al.* (2015) evaluated OSM tags in four metropolitan areas in Germany and the Global Monitoring for Environment and Security Urban Atlas data (GMESUA) (Copernicus Land Monitoring Service 2020) data set was used as the reference. Fonte and Martinho (2017) assessed the OpenStreetMap for the creation of reference databases in the

Table 2. Data cleaning strategy.

Method	Data set	Strategy
Movshovitz-Attias <i>et al.</i> (2015)	GSV	Text & Image Matching
Kang <i>et al.</i> (2018)	GSV	Pre-trained Classifier
Zhu and Newsam (2015)	Flickr	Fine-tuned Classifier, Location
Zhu <i>et al.</i> (2019)	Flickr	Fine-tuned Classifier, Location

Table 3. Land-use labeling. The rows with more than one class denote that the classification was performed in multiple levels following a coarse to fine manner.

Method	Source of Label	Feature	# Class
Estima and Painho (2013)	OSM	Polygon	5, 15, 44
Fan <i>et al.</i> (2014)	OSM	Polygon	6
Arsanjani <i>et al.</i> (2015)	OSM	Polygon	15
Liu <i>et al.</i> (2020)	OSM	Polygon	16
Arsanjani <i>et al.</i> (2013)	OSM	POI, Line, Polygon	2, 4, 15
Ye <i>et al.</i> (2019)	OSM	POI, Line	10
Estima and Painho (2015)	OSM	POI	5, 15, 44
Jiang <i>et al.</i> (2015)	Yahoo! Local	POI	14
Gao <i>et al.</i> (2017)	Foursquare	POI	-

evaluation of land-use/land cover maps. The study concluded that a small portion of the OSM-based reference data set requires photointerpretation of high-resolution imagery.

Besides OSM data, POIs have been heavily used to generate urban land-use labels for proximate sensing images. Estima and Painho (2015) explored the POI data extracted from OSM in an area of Continental Portugal. The experiments demonstrated that among the 26,191 POI examples, the agreement rate to the official land-use data is 78%. Jiang *et al.* (2015) devised a set of rules to compare POIs and map POIs provided by different data sets. The POIs were then aggregated with retail employment data. Gao *et al.* (2017) developed a statistical framework based on the latent Dirichlet allocation topic model to discover urban functional regions. The study concludes that consociating the spatial pattern distribution of POIs helps extract urban functional regions.

Combining OSM tags and POIs for data labeling has also been investigated. Arsanjani *et al.* (2013) developed a hierarchical GIS-based decision tree to generate the land-use map from OSM point, line, and polygon features. Ye *et al.* (2019) fused OSM tags, POIs, and satellite images and proposed a Hierarchical Determination method that extracts roads from OSM to generate functional units. Liu *et al.* (2020) randomly sampled points in the OSM polygons and used the OSM tags as the label for these points. This method built a semi-automatic framework to map urban land-use using OSM data.

Despite the great success of using OSM and POI data for label generation, online services that rely on voluntary contributors face issues of great inconsistency and errors. The major blemishes of OSM tags include misaligned tags with the images and buildings as well as missing annotations for buildings. To address these issues, Vargas-Muñoz *et al.* (2019) developed a tag correction method based on Markov Random Field and Convolutional Neural Network (CNN). A probability map was constructed from the correlation between tags and buildings and a CNN model was trained from building shapes to assign labels for buildings without a label.

Table 3 summarizes the existing land-use labeling methods. Among all the supplementary data sources, OSM serves as a major source for land-use annotation. However, OSM, as well as other similar service providers, allows users to define their labels (or tags). This enables the flexibility and adaptability of tagging but increases inconsistency and bewilderment of using the tagged data for land-use labeling. The alignment of the tags and the land-use types has not yet been fully studied. Label extraction, sorting, alignment, and refinement are still subjective and obscure. The development of automatic methods for land-use labeling of the proximate sensing images is needed.

3. Methods for land-use analysis

3.1. Building classification

Differentiating building usage from overhead images is ill-posed in urban settings due to the uncertainty of correspondence between rooftops and the surroundings of a building to its actual usage. Proximate sensing images enable researchers to integrate building side views, texture, and decorations (e.g. signs and sculptures) to more accurately decide the building usage.

An early exploration of associating street view images with building functions was conducted by Zamir *et al.* (2011). In this study, a set of 129,000 street view images and textual information were used to identify commercial entities. The list of businesses was generated from services such as Yellow Page and the text information detected from the street view images are matched to the business entities using Levenshtein distance. The experiments achieved an overall accuracy of 70%. Iovan *et al.* (2012) used scale-invariant feature transform (SIFT) descriptors randomly sampled from each image to create a visual dictionary. Bag of Words (BoW) model (Zhang *et al.* 2010) and Bag Of Statistical Sampling Analysis (BOSSA) model (Avila *et al.* 2011) were applied to generate image signatures. Using a kernel Support Vector Machine (SVM), the method classifies urban structures such as shops, porches, etc. Tsai *et al.* (2014) employed OpponentSIFT (Van De Sande *et al.* 2009) as image features and created a codebook using clusters of BoW features. The recognition was conducted using distributional clustering. A similar strategy was implemented by Rupali and Patil (2016), in which SIFT descriptor and clustering were used. The proposed two-phase framework recognizes the on-premise signs of business entities using street view images. Li and Zhang (2016) used the GSV images of New York City to differentiate single-family buildings, multi-family buildings, and non-residential buildings. Feature descriptors such as GIST, HoG, and SIFT-Fisher were implemented for classification. It was demonstrated that the SIFT-Fisher descriptor achieved the best accuracy of 91.82% on classifying residential and non-residential buildings.

Besides the aforementioned feature engineering methods, deep networks, especially CNN models pre-trained on large-scale data sets, have been broadly used for building function classification. Movshovitz-Attias *et al.* (2015) created a large training data set using an ontology-based labeling method, which was used to learn multi-label, fine-grained storefronts. A CNN model based on GoogLeNet was trained with ImageNet (Deng *et al.* 2009) and fine-tuned using street view images. Wang *et al.* (2017) employed AlexNet (Krizhevsky *et al.* 2012) to classify stores from street view images. Kang *et al.* (2018) used a CNN model trained with Place2 to filter out images irrelevant to buildings and employed pre-trained deep networks including AlexNet, ResNet18, ResNet34, and VGG16 for building classification. Hoffmann *et al.* (2019) performed a five-class classification using geotagged images from Flickr and supplementary building polygons from OSM. A spatial nearest neighbor classifier was developed to assign images to buildings. A VGG16 model pre-trained with ImageNet was adopted for feature extraction and a logistic regression classifier trained using SAGA optimizer (Defazio *et al.* 2014) was applied to make the final prediction.

Object detection has been employed for building classification. Hoffmann *et al.* (2019b) used a ResNet50 based the Single Shot MultiBox Detector (Liu *et al.* 2016) trained with the

COCO data set (Lin *et al.* 2014) to detect the frequently appeared objects in social media images. The rasterization was performed by counting the detected objects, the mutual information between the object frequency and the function of the nearby buildings was computed. The study found a strong correlation between the object counts in social media images and the building functions. Zhao *et al.* (2020) devised a 'Detector-Encoder-Classifier' network to detect buildings in GSV images using object detectors (Ren *et al.* 2015, Cai and Vasconcelos 2018), which were fed into a Recurrent Neural Network (RNN) for urban land-use classification. A recent study by Sharifi Noorian *et al.* (2020) implemented a framework to classify the retail storefronts using GSV images. YOLOv3 (Redmon and Farhadi 2018) was applied to detect the storefronts, then ResNet pre-trained using Places365 data set was used to further perform the classification.

Table 4 summarizes the methods for building classification. Among the available imagery data, street view images, especially GSV images, serve as a major source of proximate sensing data for building classification. Besides using conventional image features, studies conducted by Movshovitz-Attias *et al.* (2015), Wang *et al.* (2017) and Hoffmann *et al.* (2019) adopted CNN models that follow an end-to-end design and, hence, integrate feature extraction with classification. Multi-functional buildings (e.g. apartment buildings with restaurants on the ground floor) pose greater difficulty in comparison to the single functional ones, which appear often in large metropolitan and dense urban areas. The development of multi-label classification could be responsive to such a unique problem. In addition, leveraging interior photographs demonstrated the potential for fine-grained building classification but calls for further exploration.

3.2. Aggregation of proximate sensing images

The proximate sensing images are largely diverse in contents, perspectives, and field of view. Imagery data from online social networks and mapping services facilitated the practicability of aggregating various proximate sensing images to reform urban land-use classification and segmentation (Yuan *et al.* 2021). Leung and Newsam (2012) explored the Flickr images of two university campuses. Geo-tagged images are grouped based on the spatial locations, contributor, and acquisition time. Text annotations were used as auxiliary data for training an SVM classifier. Images taken from the building interior and surrounding areas provide additional clues of human activities and, hence,

Table 4. Building classification methods. 'SVI' denotes unspecified street view images and 'GSV' denotes Google street view images.

Method	Data	# of Class	Classifier	Feature
Zamir <i>et al.</i> (2011)	SVI	2	Levenshtein Dist.	Text, Gabor
Iovan <i>et al.</i> (2012)	SVI	4	SVM	SIFT, BoW, BOSSA
Wang <i>et al.</i> (2017)	SVI	8	AlexNet	Deep features
Tsai <i>et al.</i> (2014)	GSV	62	Thresholding	SIFT
Movshovitz-Attias <i>et al.</i> (2015)	GSV	208	GoogLeNet	Deep features
Rupali and Patil (2016)	GSV	62	Thresholding	SIFT
Li and Zhang (2016)	GSV	4	SVM	GIST, HOG, SIFT
Kang <i>et al.</i> (2018)	GSV	8	AlexNet, ResNet, VGG	Deep features
Zhao <i>et al.</i> (2020)	GSV	4	Cascaded R-CNN, RNN	Deep features
Sharifi Noorian <i>et al.</i> (2020)	GSV	24	YOLOv3, ResNet	Deep features
Hoffmann <i>et al.</i> (2019)	Flickr	5	Logistic Regression	Deep features

can be used as auxiliary data sources. Zhu and Newsam (2015) extended the method by differentiating indoor and outdoor images with a classifier trained with the SUN data set (Xiao *et al.* 2010) and extracting semantic features using a pre-trained CNN model. The aggregation was achieved by majority voting. Fang *et al.* (2018) integrated OSM data with geo-tagged images from social networks for urban land-use classification. The urban space is divided using the hierarchical urban street networks. Object Bank (OB) (Li *et al.* 2010) was used to extract features and predict labels to the individual image. The land-use type of each parcel is generated by the weighted sum of the image classes within the parcel. Chang *et al.* (2020) leveraged the semantic segmentation of GSV images to construct a representation for urban parcels. The features from GSV, Luojia-1, Sentinel-2A, and Baidu POIs were integrated. A random tree was implemented for classification.

To enrich the training data for the employment of deep networks, images from multiple platforms are often used. Tracewski *et al.* (2017) employed VGI images from Flickr, Panoramio, Geograph, and Instagram. A CNN trained with the aggregated data sets was fine-tuned for land-use classification. Zhu *et al.* (2019) built a large-scale, fine-grained land-use data set that include images from Flickr and Google Images. A two-stream model was developed for object recognition and scene recognition. The object stream was a CNN model pre-trained with ImageNet and the scene stream is another CNN model pre-trained with the Places365 data set (Zhou *et al.* 2014). Srivastava *et al.* (2018b) adopted CNN models for the task of multi-label building function classification. The building labels were derived from Addresses and Buildings Databases (Ministry of Infrastructure and the Environment 2020). Features of three street view images of different perspectives at each street location were extracted using a pre-trained VGG16 model for classification. It was demonstrated that aggregated network outperforms the uni-modal network and the vector stacking method. Followup studies (Srivastava *et al.* 2018a, 2020) demonstrated that using multiple images at the same location improves the accuracy of land-use classification.

Table 5 summarizes the methods that aggregate multiple approximate sensing images for urban land-use classification. Besides the conventional semantic features, BoW and OB are used for feature extraction. The dominant strategies for aggregation include feature level concatenation and averaging and decision level majority voting. The key motivation is that each image represents only a partial view of the land unit; hence, aggregating multiple views from different perspectives results in an informed decision. Apart from multi-perspective images, Leung and Newsam (2012) leveraged text information from

Table 5. Methods of land-use classification that combine proximate sensing images. GSV denotes Google Street View images; GI denotes Google Images; Deep represents deep features; Ave. denotes the average aggregator; Con. stands for concatenation.

Method	Source of Data	# of Class	Feature Level Fusion		Decision Level Fusion	
			Feature	Strategy	Classifier	Strategy
Fang <i>et al.</i> (2018)	Flickr	5	OB	–	SVM	Voting
Zhu and Newsam (2015)	Flickr	8	Deep	–	SVM	Voting
Zhu <i>et al.</i> (2019)	Flickr/GI	45	Deep	–	ResNet	Ave.
Leung and Newsam (2012)	Flickr	3	BoW	Ave	SVM	–
Srivastava <i>et al.</i> (2018a)	GSV	13	Deep	Ave	SVM, MLP	Voting
Srivastava <i>et al.</i> (2018b)	GSV	9	Deep	Con.	VGG16	–
Srivastava <i>et al.</i> (2020)	GSV	16	Deep	Ave/Max	VGG	–
Chang <i>et al.</i> (2020)	GSV	5	Numeric	Con.	–	–

Flickr as an auxiliary source of information, which demonstrated the feasibility of integrating dramatically different information for improved performance.

3.3. Integrating images of different perspectives

An intuitive way to integrate images of different perspectives is by constructing a pixel-level land-use map. Workman *et al.* (2017) combined overhead and proximate images for land-use, building function classification, and building age estimation. The data set consists of GSV, Bing Map, and official city planning information. Two pre-trained VGG-16 models were used to extract features from street view images as well as overhead images. Hypercolumn was extracted from the feature maps using PixelNet (Bansal *et al.* 2017). It was demonstrated that the top-1 accuracy of land-use classification by combining overhead and proximate sensing images achieved an improvement of 11.2%. Cao and Qiu (2018) extracted the features of street view images using PlacesCNN and used Nadaraya-Watson kernel regression for spatial interpolation. After constructing the ground feature map, a SegNet (Badrinarayanan *et al.* 2017) based network is used to integrate the overhead imagery and ground feature map and perform the land-use classification. The proposed network contains two VGG16 based encoders that produce a pixel-level urban land-use map with a decoder. Feng *et al.* (2018) developed a multi-view CNN for pixel-level segmentation. In this network, lower-order potentials were used for processing overhead images and higher-order potentials were used for proximate sensing images. Feature stacking was used to achieve the fusion of proximate sensing and overhead images.

An alternative strategy is deciding land-use types for each parcel. Zhang *et al.* (2017b) developed an urban land-use data set including overhead LiDAR, high-resolution orthoimagery (HRO), GSV, and parcel data. The method assumes that the existence of text in the street view images is an essential indicator to differentiate residential and non-residential buildings, which was achieved by classifying GSV images for text detection. The classification accuracy achieved an improvement of 29.4% in classifying mix residential buildings. Huang *et al.* (2020) applied pre-trained DeepLabV3+ (Chen *et al.* 2018) and ResNet-50 (He *et al.* 2016) on satellite and GSV imagery to learn land cover proportion and scene category of each parcel. Features extracted from building footprint, POI, and check-in data were fed into an XGBoost classifier for urban land-use classification.

Research has been conducted to associating proximate sensing images to urban objects or buildings for land-use mapping. Srivastava *et al.* (2019) associated the GSV images with urban-object footprints extracted from OSM. The proposed method integrated overhead and proximate sensing images with a two-stream CNN model: a patch-based classification (Penatti *et al.* 2015) for extracting features from overhead images and a Siamese model (Bromley *et al.* 1994) for proximate sensing images. It was demonstrated that multi-model CNN models outperform uni-modal CNN models. The overall accuracy was at 75.07%. Hoffmann *et al.* (2019a) use the building function information provided by OSM and associate it with corresponding GSV and overhead images. Two fusion strategies were implemented: geometric feature fusion and decision fusion. Geometric feature fusion follows the two-stream model and the decision-level fusion model is based on model blending and stacking. The experiments demonstrated the decision fusion outperformed the feature fusion model.

Table 6 summarizes the methods that integrate images acquired from different perspectives (i.e. proximate sensing images and remote sensing images). Most of the methods extract and combine features from street view and satellite images via concatenation. Hoffmann *et al.* (2019a) developed a method for both feature level and decision level fusions. In the proposed method, decision fusion was achieved by tallying class scores. The advantage appears to be incremental. Besides satellite images, LiDAR data were also used. Yet, the results are very limited.

4. Conclusion

4.1. Discussion

Table 7 summarizes the methods for land-use classification. The column ‘number of Images’ reports the number of proximate sensing images used in the studies. The numbers in italic are precision instead of accuracy. The results by Li and Zhang (2016) report two cases: residential building vs non-residential building and single-family building vs multi-family building. Hence, the accuracy is reported separately. In the studies conducted by Workman *et al.* (2017), the accuracy includes the combination of the number of classes and the number of examples used. In the case of Cao *et al.* (2018) and Srivastava *et al.* (2019), two data sets from different locations were used in the evaluation, which produced different results.

We organize the methods according to the problems they address and the primary data sets used. The experimental settings of the evaluation (e.g. number of classes and training images) vary greatly, which makes it difficult to draw a conclusion on the state-of-the-art performance. From the perspective of applications, the average and median accuracy of building classification are 75.15% and 76.21%, respectively, and the average and median precision of building classification are 67.55% and 68.6%, respectively. For the ground-view aggregation, the average and median accuracies are 65.31% and 69.05%, respectively. For cross-view integration, the average and median accuracies are 68.01% and 74.87%, respectively. It is clear that when a large number of classes exists (e.g. 20 or more classes), the average accuracy is inferior to the cases where a smaller number of classes needs to be differentiated. For example, in the case of a large number of classes, the best accuracy for building classification is 45.01%, which is less than half of the best accuracy of the cases with a small number of classes.

Table 6. Methods of land-use classification that combine data of cross-view modalities. Prox. and Over. denotes proximate and overhead data, respectively. Strat. stands for strategies used in the corresponding method. GSV denotes Google Street View images. Deep represents deep features. Con. stands for concatenation. A/C denotes the average and concatenation.

Method	Prox. Data	Overhead Data	# of Class	Feature Fusion		Decision Fusion	
				Feature	Strat.	Classifier	Strat.
Zhang <i>et al.</i> (2017a)	GSV	LiDAR/Sat.	7	Numeric	Con.	RF	–
Workman <i>et al.</i> (2017)	GSV	Satellite	206	Deep	Con.	MLP	–
Workman <i>et al.</i> (2017)	GSV	Satellite	11	Deep	Con.	MLP	–
Cao <i>et al.</i> (2018)	GSV	Satellite	13	Deep	Con.	SegNet	–
Srivastava <i>et al.</i> (2019)	GSV	Satellite	16	Deep	Con.	VGG	–
Hoffmann <i>et al.</i> (2019a)	GSV	Satellite	4	Deep	A/C	VGG	A/C
Huang <i>et al.</i> (2020)	GSV	Satellite	8	Deep	Con.	XGBoost	–

Table 7. Accuracy/precision (%) comparison of land-use classification methods using proximate sensing images. ‘Number of Images’ only includes the number of proximate sensing images used in corresponding researches. SVI denotes unspecified street view images. GSV denotes Google street view images. GI stands for Google Images. The entries Enclosed in parentheses indicate precision is reported instead of accuracy.

Problem	Method	Source of Data	# of Classes	# of Images	Acc. (Prec.)
Building Classification	Zamir <i>et al.</i> (2011)	SVI	2	129,000	70.00
	Li and Zhang (2016)	GSV	2	1,048	74.30
	Li and Zhang (2016)	GSV	2	1,048	91.82
	Iovan <i>et al.</i> (2012)	SVI	4	1,516	76.21
	Wang <i>et al.</i> (2017)	SVI	8	4,636	93.60
	Sharifi Noorian <i>et al.</i> (2020)	GSV	24	1,200	45.01
	Kang <i>et al.</i> (2018)	GSV	8	19,658	(59.00)
	Hoffmann <i>et al.</i> (2019)	Flickr	5	343,600	(67.00)
	Zhao <i>et al.</i> (2020)	GSV	4	19,070	(81.81)
	Rupali and Patil (2016)	GSV	62	4,649	(68.86)
Ground-View Aggregation	Tsai <i>et al.</i> (2014)	GSV	62	4,649	(68.60)
	Movshovitz-Attias <i>et al.</i> (2015)	GSV	208	1,300,000	(63.00)
	Fang <i>et al.</i> (2018)	Flickr	5	24,835	76.50
	Chang <i>et al.</i> (2020)	GSV	5	–	79.13
	Zhu and Newsam (2015)	Flickr	8	37,784	76.00
	Srivastava <i>et al.</i> (2018b)	GSV	9	–	44.41
	Srivastava <i>et al.</i> (2018a)	GSV	13	3,4261	69.05
	Srivastava <i>et al.</i> (2020)	GSV	16	4,4957	62.52
	Zhu <i>et al.</i> (2019)	Flickr/GI	45	58,418	49.54
	Zhang <i>et al.</i> (2017a)	GSV	7	–	77.50
Cross-View Integration	Huang <i>et al.</i> (2020)	GSV	8	660,000	74.20
	Workman <i>et al.</i> (2017)	GSV	11	139,327	77.40
	Workman <i>et al.</i> (2017)	GSV	11	38,603	70.55
	Cao <i>et al.</i> (2018)	GSV	13	139,327	78.10
	Cao <i>et al.</i> (2018)	GSV	13	38,603	74.87
	Srivastava <i>et al.</i> (2019)	GSV	16	44,957	73.44
	Srivastava <i>et al.</i> (2019)	GSV	16	9,908	75.07
	Workman <i>et al.</i> (2017)	GSV	206	38,603	34.13
Hoffmann <i>et al.</i> (2019a)	Workman <i>et al.</i> (2017)	GSV	206	139,327	44.88
	Hoffmann <i>et al.</i> (2019a)	GSV	4	225,036	(76.00)

Although accuracy and precision are usually reported in the reviewed papers, the overall accuracy or precision could be misleading in multi-class classification. It is possible that the overall accuracy might be quite high, but one class or a few classes have much greater errors. If the accuracy of those very classes is the most important to the user, the results are unacceptable despite the high overall accuracy. Among the reviewed methods, when a small number of classes exists, the accuracy could be greater than 90%. However, the average and median accuracy among all (without considering the factors listed in Table 7) are 69.1% and 74.3%, respectively. It is expected that this median accuracy is improved in future studies.

The gap between rich data sets and lack of labeled examples makes data annotation a pressing need. The adopted land-use types, however, are highly diverse. As shown in Table 7, the number of classes ranges from two up to more than two hundred. Most studies adopt two ways to define land-use types for proximate sensing images: 1) a data-driven approach that defines land-use types based on the function of the structures in the image (Zhu and Newsam 2015) and selects the proximate sensing images that fit the land-use types (Kang *et al.* 2018, Zhao *et al.* 2020), and 2) a systematic approach that leverages the published urban land-use data to design land-use types, e.g. Workman *et al.* (2017)

followed the documentation of New York City Department of City Planning and Zhu *et al.* (2019) adopted the Land Based Classification Standards to generate land-use types. The data-driven approaches provide a specialized set of classes for the available data, whereas systematic approaches are based on standardized land-use conventions that are mostly uniform and avoid inconsistency.

Proximate sensing images, especially VGI data are often biased to the prosperous areas of the cities, such as landmarks and attractions. This leads to imbalanced data and negative impacts on learning. Strategies to circumvent this problem include gathering more data from unpopular regions (Srivastava *et al.* 2018a, 2018b) and integrating supplemental data sets (Zhu and Newsam 2015, Zhu *et al.* 2019). A related problem is a gap between land-use maps and sparsely distributed VGI images for pixel-level land-use classification (Fang *et al.* 2018). Kernel regression and density estimation are used to convert the imbalanced image features into a dense feature map that is aligned with the pixel-level land-use map (Workman *et al.* 2017, Feng *et al.* 2018, Cao and Qiu 2018).

With the vigorous development of deep learning methods, CNNs and the variants have been widely adopted and extended for both data preparation (Vargas-Muñoz *et al.* 2019) and land-use classification. The dominant strategy of using deep networks is fine-tuning a pre-trained model with proximate sensing examples, a.k.a., transfer learning strategy. The rationale is two-fold: lack of a sufficiently large training set and high computational demand for training from scratch. Transfer learning addresses the problems fairly successfully. However, models trained with a data set of one problem are unlikely to be optimal to address a different problem (Qiao *et al.* 2020). Our understanding of the capability of transfer learning is limited. For example, questions such as what the criteria are to ensure the success of transfer learning and how much refinement is needed to align the model with the new problem demand further investigations.

A loosely related but important aspect of land-use analysis using proximate sensing data is the ethical implication. The collection and sharing of proximate sensing data involve privacy and trust of anonyms. With a wide application of smartphones and dash-cams, images with embedded metadata are collected automatically, which are shared via online social networks. In addition, sensitive personal information such as license plates and biometric data is captured without consent. Enterprises have developed policies and measures to address the privacy issues by blurring pedestrian faces and license plate numbers and allowing users to submit requests to remove or obfuscate personal information, e.g. face and home view. A similar practice is implemented in platforms such as OpenStreetCam. Another aspect is related to the commitment and professionalism of the contributors. The open platforms that allow users to upload images and videos voluntarily face challenges in ensuring data quality. Users contribute to data without risking the irrevocable consequences. This necessitates the data cleaning process for using imagery data from open platforms as well as studies to evaluate the quality of data (Mahabir *et al.* 2020b).

4.2. Summary and future work

The urban landscape is shaped by the activities of the inhabitants. The emergence of proximate sensing images has spurred many inspiring studies for better urban land-use analysis. This paper presents the proximate sensing data sets and methods for urban land-

use analysis. Despite the great advancements, urban land-use analysis using proximate sensing images remains a research area with many technical challenges. To date, well-annotated data sets suitable for method development and evaluation are very limited. The voluntary nature of most proximate sensing data sets calls for development and solutions to improve data quality and data annotation. The demand for inclusive, consistent, high-quality benchmark data is a pressing need. Automatic urban land-use annotation, refinement, sorting, and alignment of labels remain open challenges and non-trivial tasks.

Several data refinement techniques were developed such as leveraging text, location, polygonal outline information to remove unusable data. Alternatively, using a pre-trained and fine-tuned model to filter out the irrelevant images is an acceptable approach. To automate the process of generating land-use annotations (labels), OSM tagging, and POI information demonstrated effectiveness in the form of auxiliary information for urban land-use labeling. Unsupervised or semi-supervised learning strategies need further investigation and validation.

To leverage complementary remote sensing data, methods that integrate images of different perspectives and modalities have been developed. In addition to the conventional image features such as SIFT, HOG, GIST, and BoW, deep features have been extensively explored. Image features are extracted and fused to form a consolidated input to the classifier. Alternatively, decision level fusion combines land-use predictions from multiple classifiers via majority voting or Softmax integration. The studies demonstrated the effectiveness of using proximate sensing images for urban land-use analysis, especially for differentiating residential and commercial entities and fine-grained urban land-use classification.

In addition to developing annotation-independent frameworks, introducing supplementary data, e.g. Google Images filtered by keywords, or the land-use related entries in large-scale scene data sets could help to boost the model performance for land-use classification tasks. The majority of deep learning-based methods rely on the pre-trained CNN. Extending recent, advanced network design strategies such as multi-scale frameworks or attention modules are promising for improving model performance.

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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