Cadastral Boundary Delineation using Deep Learning and Remote Sensing Imagery: State of the Art and Future Developments

Jeroen GRIFT, Claudio PERSELLO, Mila KOEVA

SUMMARY

Global estimates indicate that 70-75% of the people worldwide do not have access to a legal land administration system. The absence of such a system has a negative impact on essential developments such as tenure security, agricultural productivity, and sustainable development. Therefore, the UN included the formal registration of property rights, ownership, and value in several targets of the sustainable development goals. A concept that tries to speed up the registration of legal land rights is fit-for-purpose land administration. Leading principles in this approach are the use of visible cadastral boundaries and the delineation of these boundaries by using remote sensing imagery. In recent years, these principles have resulted in a growing demand for automated cadastral boundary extraction methods. Recent studies on cadastral boundary extraction using deep learning and remote sensing imagery look promising. However, the number of studies is limited. Recent studies are based on small study areas and small data sets, did not implement state-of-the-art deep learning models, and did not investigate the transferability and generalization ability of the models to other geographical locations. This paper reviews the applications of deep learning and remote sensing imagery for cadastral mapping and describes several research gaps. Possible improvements include building benchmark datasets, evaluating the proportion of visible/invisible boundaries in these benchmark datasets by analyzing the overlap between cadastral and topographical boundaries, applying deep learning applications from other remote sensing fields for cadastral mapping, and creating human-in-the-loop deep learning pipelines.

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1   INTRODUCTION

According to global estimates, 70-75% of the people in the world do not have access to a legal land administration system that records and protects their land rights (FIG & The World Bank, 2014; McLaren, 2015). The absence of such a formal system has a negative impact on tenure security, agricultural productivity, sustainable development, land market effectivity, gross national product, and other essential developments (UN-Habitat, 2012; Williamson, 1997). Because of this negative impact, the formal registration of property rights, ownership, and value is incorporated in several targets (1.4, 2.3, 2.4) of the sustainable development goals of 2030 (Koeva et al., 2021; Persello et al., 2022; United Nations, 2015).

The lack of a formal land administration system is partially caused by technological issues (Luo, Bennett, Koeva, & Lemmen, 2017). In recent decades, conventional ground-based survey methods have helped high-income countries to build up countrywide cadastral maps with high accuracies. However, this approach is too labor-intensive and expensive for most mid and low-income countries and could take several decades to complete. Therefore, in the last decade, the concept of fit-for-purpose land administration (FFPLA) has been introduced and tested (FIG & The World Bank, 2014; UN-Habitat, 2016). FFPLA focuses on visible cadastral boundaries and delineating these boundaries with remotely sensed data. The idea behind these principles is that cadastral boundaries often intersect with physical objects such as roads, fences, buildings, and vegetation and that remote sensing images are available worldwide, relatively cheap, and updated regularly (Kohli et al., 2017; Luo, Bennett, Koeva, Lemmen, et al., 2017). FFPLA has resulted in a growing demand for automated cadastral boundary extraction methods in recent years (Kelm et al., 2021; Lemmen et al., 2017).

Recent studies on cadastral boundary extraction using deep learning and remote sensing data show promising results (Crommelinck et al., 2019; Fetai et al., 2021; Xia et al., 2019). Deep learning models are composed of multiple layers that learn data representations at different levels of abstraction, from pixels, corners, and edges up to complex spatial patterns (LeCun et al., 2015; Persello & Stein, 2017). Although the studies on deep learning-based cadastral boundary delineation look promising, the number of studies is limited. The main limitations of the studies are the small amount of tested state-of-the-art deep learning models, the relatively small study areas on which the models were trained, and the absence of research on the transferability and generalization of the models to other locations.

The next chapter includes background information on land administration, cadastral boundaries, FFPLA, automated extraction of boundaries, and deep learning. Chapter 3 describes the state of the art for topics such as the overlap between cadastral boundaries and topographical objects and indirect cadastral mapping of visible boundaries. The concluding chapter will describe the research gap and possible future developments.

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2   BACKGROUND

2.1   Land administration and cadastre

Land administration is defined as: "public sector activities required to support alienation, development, use, valuation, and transfer of land" (Dale & McLaughlin, 1999, p. 1). According to the land administration guidelines from the United Nations, land administration plays a vital role in guaranteeing land ownership and tenure security, land market development, land consolidation, urban planning, and sustainable management of the environment (United Nations, 1996).

An essential step in land administration is recording the spatial extents of land parcels and their related ownership rights (Lemmen et al., 2015). This land parcel recordation is often done with the help of a cadastral system, which is formally known as an information system that contains geographical descriptions of the land parcels and the associated rights, restrictions, and responsibilities, such as the nature of the parcel, its ownership, and the value and its improvements (FIG, 1995). Most high-income countries have invested for centuries in mature land administration systems that protect people-to-land relationships (Enemark et al., 2021). However, in mid and low-income countries, these formal systems are often absent. Global estimates show that approximately 70% of the world's population cannot access a legal land administration system (FIG & The World Bank, 2014; McLaren, 2015).

2.2   Cadastral boundaries and cadastral mapping

To accurately map the extent of the land parcels, cadastral boundaries must be identified, demarcated, measured, and mapped. A cadastral boundary is defined as: "an imaginary line that divides two adjoining estates while in common language, the term denotes the physical objects by reference to which this line is described" (Dale & McLaughlin, 1999, p. 50). Mapping these cadastral boundaries can be performed in two ways: by defining fixed boundaries with direct surveying technologies or by defining general boundaries with mostly indirect surveying technologies (Ali et al., 2012; Tuladhar, 1996).

The fixed boundary approach is based on the principle that all cadastral boundaries are accurately measured and fixed on the ground using a global navigation satellite system (GNSS), a total station, or more conventional methods such as a theodolite in combination with a surveyor's chain. When insufficient physical objects are available around the measured site, cadastral boundaries are demarcated with fences, iron pipes, stones, or other physical markers. The advantage of this approach is that landowners know the exact extent of their property.

The general boundary approach is less focused on the accurate position of cadastral boundaries and uses mainly indirect surveying techniques to delineate and extract cadastral boundaries. Primary sources for these techniques are satellite, aerial, and unmanned aerial vehicles (UAVs) imagery (Luo, Bennett, Koeva, & Lemmen, 2017). With the help of these sources, it is straightforward to delineate visible cadastral boundaries that coincide with physical objects such as buildings, fences, hedges, rivers, and roads (Crommelinck et al., 2016). The main advantage of this approach is that it is faster and cheaper than the fixed boundary approach.

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2.3 Fit-for-purpose land administration

The term "Fit-for-purpose" refers to the principle that land administration in mid- and low-income countries should be adapted to the needs of the inhabitants, such as ensuring tenure security and land use planning, instead of focusing on accuracy and top-end technical applications (FIG & The World Bank, 2014). The FFPLA approach includes a spatial framework that uses the following principles (UN-Habitat, 2016):

- Use visible/physical general cadastral boundaries instead of fixed cadastral boundaries.
- Use remotely sensed data instead of ground-based measurements
- Quality depends on the purpose rather than on technical possibilities
- Support for ongoing updating, upgrading, and improvement

By following these principles, it should be possible to map the visible cadastral boundaries in a fast, interactive, and affordable way. It can have a significant impact on closing the land tenure gap. These principles have resulted in a growing demand for automated extraction of visible cadastral boundaries. The following section will give some background on this topic.

2.4 Automated extraction of boundaries and deep learning

Techniques or methods that could automatically extract boundaries from imagery are either unsupervised or supervised. Unsupervised methods transform input images into output data without the help of labeled data, while supervised methods use labeled data to transform input data into output data. The most common supervised methods nowadays are deep learning methods, which are used for natural language processing, object detection, and image segmentation (Chollet, 2018). Deep learning applications have been so successful in the past decade that they have replaced the traditional, not deep learning-based supervised and unsupervised methods on a large scale.

Their deep structure and unique architecture, along with the development of new hardware (in the form of graphics processing units (GPUs)) and the introduction of benchmark datasets, were the driving forces behind the shift from traditional boundary extraction methods to deep learning-based methods (Goodfellow et al., 2017). Deep learning is based on the concept of representational learning. Representational learning is an approach to learning suitable data representations necessary for classifying input data (LeCun et al., 2015). A deep learning model determines these representations by stacking non-linear modules in a layer-by-layer architecture. Every layer transforms the representations from a lower to a higher level of abstraction. Compared with traditional methods, the most significant advantage of deep learning models is that all the representations are learned in a supervised way and not handcrafted by a human operator.

The different representations are calculated in the training stage (Figure 1). First, a feedforward pass takes input data and their corresponding labels and computes the representations in the other layers. Second, together with a loss function, these representations are used to predict unseen data. Finally, the loss function is lowered by an optimizer that adjusts the internal model weights. These weights contain the "knowledge" of the model. Deep learning models often have millions of these model weights, and manually adjusting these weights is too

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expensive. The model computes a gradient vector of the weights to overcome this problem. Doing this makes it possible to determine the direction the error will move if you adjust the weight slightly in a particular direction (LeCun et al., 2015). The weights are changed in the opposite direction of the gradient to lower the error function. The error function will finally reach its minimum value by repeating this process. The remainder of this section will describe the most popular types of deep learning models regarding boundary extraction from imagery.
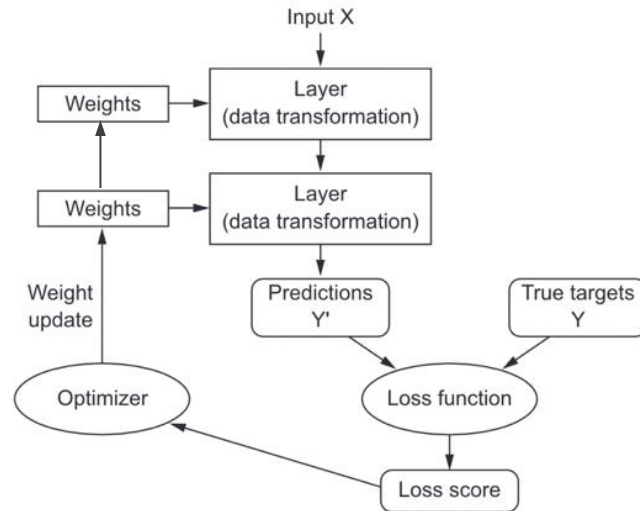

Figure 1. Training a neural network (Chollet, 2018, p. 11)

2.4.1 *Convolutional neural networks*

A deep learning architecture often used in image analysis is the convolutional neural network (CNN). It was introduced by LeCun et al. (1998). Still, its breakthrough came in 2012 when Krizhevsky et al. (2012) outperformed state-of-the-art classifiers by introducing AlexNet, a version of the CNN introduced by LeCun et al. (1998). Three main components defined this CNN: convolutional, pooling, and fully connected layers.

Convolution in the context of image processing refers to the transformation of an image by applying a moving window over each pixel and its direct neighbors (Figure 2). This moving window is often called a convolutional filter. The filter size and pixel values determine the output image that is produced. Applying a single convolutional filter results in a single modified image called a feature map. Important to mention is that the values in the convolutional filter are the trainable weights of the network. The weights in the filter determine how important a pixel is when calculating a feature map. Edge filters are common in the first convolutional layer of a CNN. More abstract filters are found when going deeper into the network. Stacking multiple convolutional layers often results in more parameters that must be trained. Training more weights increases the processing time and the complexity of the training stage. This complexity is often reduced by using pooling layers. Pooling layers reduce the number of

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weights in a network by using a downsampling strategy. Examples of pooling functions are average pooling and max pooling. The final main component of a CNN is the fully connected layer. This layer is placed after the last pooling layer. The feature maps from the last pooling layer are converted into a flattened one-dimensional array. This flattened array is fed into a multi-layer perceptron (MLP). The MLP contains hidden layers and an output layer. Each hidden layer contains several neurons connected to all the neurons in the next hidden layer. A weight value accompanies the connections between the nodes. The greater the value of this weight, the higher its influence on the final prediction. The goal of adjusting these weights is the same as those in the convolutional filters: get the lowest error possible. The output layer calculates the final prediction, and its type depends on the prediction you want.

2.4.2   Fully convolutional networks

A special type of CNN is the so-called fully convolutional network (FCN). The novelty of this model is the ability to perform semantic segmentation, which means that all pixels in the input image are classified. The CNN introduced in the previous subsection primarily focuses on image classification, which intends to label a complete image to a single class. An FCN is focused on semantic segmentation and labels each pixel individually.

The idea of an FCN was introduced by Long et al. (2015). In their proposed architecture, they used an encoder-style architecture. The encoder uses a sequence of convolutional layers, rectified linear unit (ReLU) activation functions, and pooling layers to downsample the data into feature maps that are not flattened (like in AlexNet) but that retain their 3-dimensional structure. Although these feature maps could directly be used for pixel classification, an experiment showed that upsampling the feature maps and connecting the upsampled part with the finer layer in the decoder with the same dimensions could increase the quality of the predictions. These connections are called skip connections.

A slightly different model called U-Net is based on the conventional FCN developed by Long et al. (2015) and was introduced by Ronneberger et al. (2015). The model has a symmetrical U-shape and is therefore called U-Net (Figure 2). The main modification in U-Net is that the decoder part contains more feature maps than a conventional FCN. All convolutional layers in the encoder part are connected to the corresponding deconvolution layer in the decoder part. Consequently, context information is preserved in layers with higher resolution. Like the conventional FCN architecture, the U-Net model's main benefits are that it can take input images of arbitrary size, predict images from the same size relatively quickly, and perform relatively well when input data is scarce.

2.4.3   Vision transformers

A downside of the models relying on convolutional kernels is their relatively small receptive field and lack of global context modeling (Wang et al., 2022). A model that tries to overcome this problem was introduced by Dosovitskiy et al. (2021). Their vision transformer (ViT) model contains an adjusted transformer, the state-of-the-art natural language processing (NLP) model. Several studies in building extraction applied transformer-based models and produced results that outperformed convolution-based models (Qiu et al., 2022; Wang et al., 2022). More information on ViT and transformers in general can be found in Vaswani et al. 2017), Dosovitskiy et al. (2021), and Liu et al. (2021)

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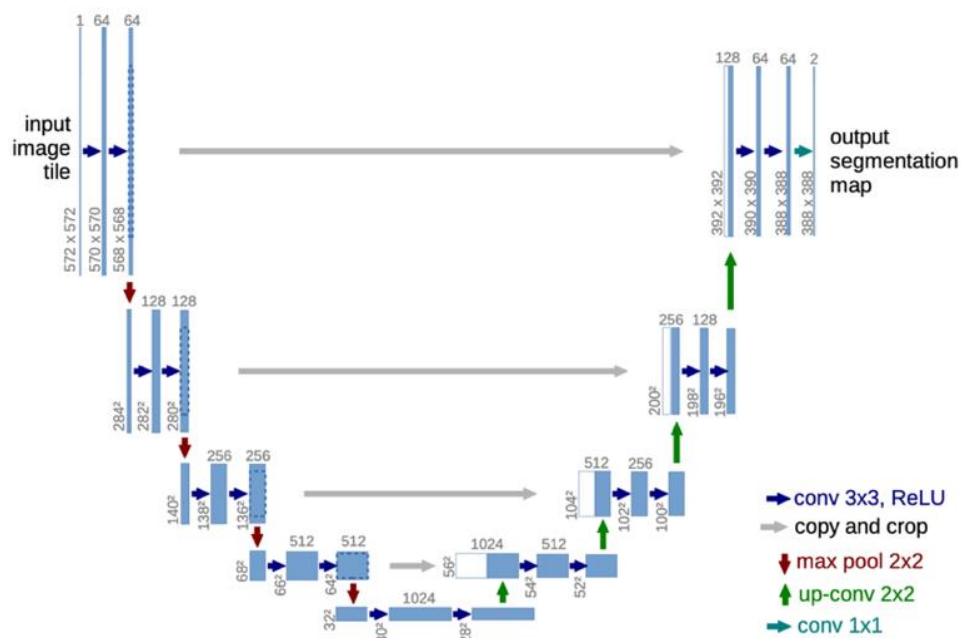Orlando, Florida, USA, 28 May–1 June 2023

Figure 2. The U-Net model (Ronneberger et al., 2015, p. 2).

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3   STATE OF THE ART

3.1   Overlap between cadastral boundaries and topographical objects

A definition of a cadastral boundary was provided in section 2.2. However, this definition does not tell us something about the morphological characteristics of a cadastral boundary. Several studies investigated these characteristics. These studies aimed to determine the proportion of visible/invisible cadastral boundaries to check whether cadastral boundaries could be extracted automatically. If a large portion of the cadastral boundaries is visible, automated extraction methods will likely be more successful.

Kohli et al. (2017) explored cadastral parcel characteristics and the overlap between visible objects and cadastral reference data in rural, peri-urban, and urban areas in Ethiopia, Ghana, Kenya, and several other countries. The fraction of visible cadastral parcels ranged from zero to around 71%. A limitation of the study is that parcels were only marked as visible if the complete parcel was visible. A way to solve this problem is by using shorter cadastral boundaries as the primary entity instead of cadastral parcels. Luo, Bennett, Koeva, Lemmen, et al. (2017) investigated the overlap between cadastral boundaries and visible objects on the island of Vanuatu. Results showed that large portions of the cadastral boundaries overlapped visible objects. Over 46% of the cadastral boundaries in urban regions overlapped with road edges and 35% with building outlines. Suburban areas showed a slightly different pattern. In these regions, 25% of the boundaries coincided with fences and 49% with roads. Finally, van Beek (2015) investigated the characteristics of cadastral boundaries in the municipality of Best, the Netherlands. The approach was based on an overlay between cadastral reference data and the topographic map of the Netherlands (Basisregistratie Grootschalige Topografie (BGT)). The results showed that 90% of the cadastral reference boundaries coincided with topographic objects. Cadastral boundaries often coincided with water bodies, roads, and agricultural fields.

The studies reviewed in this section indicate a substantial overlap between cadastral reference data and topographic objects. However, the analyzed visible cadastral boundaries may not represent all the cadastral boundaries in the world. Due to differences in landscape, exploring the boundary morphology of a specific study area could be helpful when automatic boundary extraction is applied.

3.2   Indirect mapping of visible cadastral boundaries

Bennett et al. (2021) investigated the development of indirect surveying techniques regarding land administration. The authors state that indirect surveying using photogrammetry and remote sensing has a long tradition in land administration and is an essential part of cadastral mapping. It is crucial because it opens the way for automated delineation of cadastral boundaries. Several studies investigated this automation by applying image analysis techniques. These techniques are classified into manual, traditional, and deep learning methods and will all be discussed in the remainder of this section.

Manual indirect cadastral mapping is carried out by an operator who delineates cadastral boundaries from satellite/aerial imagery in, for example, a GIS. Lemmen et al. (2009) used high-resolution satellite imagery (HRSI) printed on paper and carried out to the field to delineate cadastral parcels by pen. Additional GNSS measurements were collected to improve

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the positioning of the imagery. Other steps in the process were map scanning, importing the maps into a GIS, georeferencing the maps, and delineating the parcel boundaries drawn by pen. This approach is often called participatory mapping. Although the approach is straightforward to implement by local people, it could be improved by directly drawing the parcels on a handheld device with a GIS installed. Ali et al. (2012) also investigated using HRSI and GNSS measurements for cadastral mapping. Both data sources were imported in a GIS and were used by stakeholders to delineate cadastral parcel boundaries. Results showed that adding HRSI to the cadastral mapping pipeline resulted in a shorter processing time than direct cadastral mapping. Another manual method was tested by Rao et al. (2014). They used GNSS data and HRSI to identify cadastral parcel boundaries. Accuracy assessments showed that 80% of the delineated cadastral boundaries met the accuracy standards for cadastral maps. The study also showed that accuracy increased when moving to higher spatial resolution.

Advances in image resolution and image analysis techniques opened new ways toward automated cadastral mapping. Estimates showed that 30-60% of an initial land administration project is spent on cadastral mapping (Burns, 2007). Therefore, expenses and time could be saved by automating a part of the cadastral mapping process. A considerable amount of literature has been published on automated cadastral mapping. (Crommelinck, Bennett, Gerke, Yang, et al. (2017) used the gPb contour detector for cadastral boundary extraction. The results showed correctness and completeness values of around 80%. Another study by Wassie et al. (2017) investigated the application of a mean-shift segmentation algorithm on HRSI to extract cadastral boundaries. The main benefit of this approach over the latter is that the output is in vector format. The results showed that the algorithm could extract visible cadastral boundaries in rural areas. Crommelinck et al. (2018) proposed a semi-automated cadastral mapping pipeline. This pipeline starts with extracting candidate cadastral boundaries by combining a gPb contour detector and a simple linear iterative clustering algorithm with a classification module (Crommelinck, Bennett, Gerke, Koeva, et al., 2017; Crommelinck, Bennett, Gerke, Yang, et al., 2017). Next, a least-cost path algorithm is used to assist a human operator with converting the extracted features into final cadastral boundaries. The results showed that clicks decreased by 86% compared with manual delineation, a considerable contribution towards automation. A different approach was proposed by Fetai et al. (2019). This study investigated the potential of UAVs imagery and the ENVI feature extraction module concerning visible cadastral boundary mapping. The results showed correctness of around 80%. Finally, a study by Nyandwi et al. (2019) used MRS to extract cadastral boundaries from HRSI in urban and rural areas. The results for rural areas looked promising, with values of 47.4% and 45% for automated extraction correctness and completeness against 74.3% and 70.4% for manual extraction correctness and completeness. The study also showed that indirect mapping of cadastral boundaries in urban areas is challenging and inaccurate.

Although relatively high-quality output could be generated with the previously mentioned examples, these methods heavily rely on tuning segmentation parameters (Fetai et al., 2021). Setting these parameters can be highly labor-intensive (Persello & Stein, 2017). A way to overcome this problem is to use deep learning. Deep learning does not rely on predefined segmentation parameters but learns feature representations based on input data and their corresponding labels. A couple of studies are devoted to applying deep learning to cadastral mapping. A study by Crommelinck et al. (2019) used a CNN to classify segmented high-

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resolution UAV images into candidate cadastral boundaries. The results showed that the CNN approach required 38% less processing time and 80% fewer clicks than the manual delineation of visible cadastral boundaries. Another study by Xia et al. (2019) used an FCN to classify UAV images into binary masks of boundary/non-boundary (Figure 3). The study results showed that the FCN could accurately detect visible cadastral boundaries. The proposed method could minimize human interaction during cadastral mapping and reduce the required field trips.
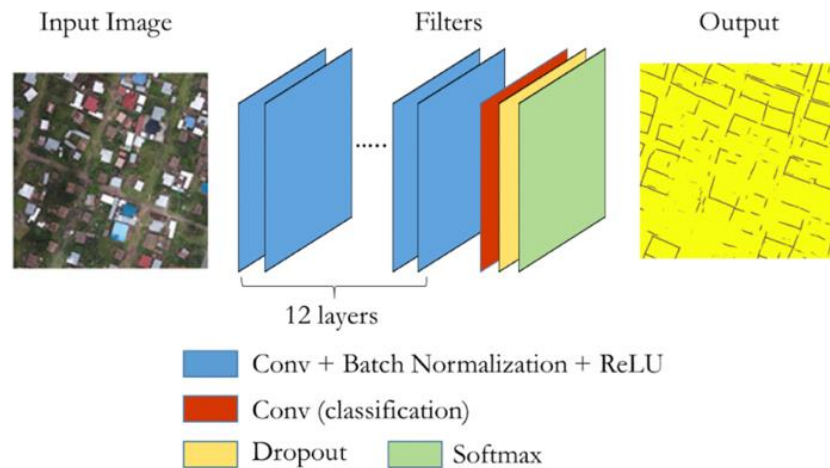

Figure 3. FCN-based cadastral boundary extraction model (Xia et al., 2019, p. 6)

Fetai et al. (2021) investigated the difference between open-source deep learning software libraries (a TensorFlow U-Net implementation) and commercial deep learning software (ENVINet5) when applied to visible cadastral boundary extraction. The open-source implementation showed slightly better results. Finally, (Wudye, 2022) investigated the possibility of an end-to-end visible cadastral boundary delineation with vector output. The proposed method uses U-Net as a backbone to perform semantic segmentation. The feature maps generated by the backbone are directed into two streams. One stream creates interior and edge masks. The other stream takes the input of the first stream and the feature maps and uses this information to calculate direction information using a frame field. The output of these two streams is used to complete several polygonization steps. The results showed that the vector output has a regular and simplified shape compared with conventional pixel-based models.

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4 CONCLUSION

Looking at the previously described topics and studies, one can observe that few studies have investigated the application of deep learning methods and remote sensing imagery for cadastral boundary delineation. The studies on this topic showed that deep learning using remote sensing imagery could significantly improve the automated extraction of visible cadastral boundaries compared to not deep learning-based extraction methods. Considering the limitations of the current cadastral boundary delineation applications and the opportunities noticed in reviewed related research fields, the following gaps and challenges were identified:

- Only a few deep learning methods have been investigated for cadastral boundary delineation. It is essential to apply state-of-the-art techniques such as ViTs to cadastral boundary extraction to achieve the highest possible accuracy.
- Current methods for cadastral boundary delineation using deep learning and remote sensing are mainly based on raster output. To the best of the author's knowledge, only one study investigated vector output. Making predictions in vector format makes extra postprocessing steps superfluous.
- There is no benchmark dataset available for cadastral boundary delineation. Benchmark datasets are available for emerging fields such as building extraction and help the community to train and test state-of-the-art models. For cadastral boundary delineation, this is not the case.
- Relatively small datasets have been used in cadastral boundary delineation studies. The absence of a benchmark dataset could cause this. Because of these relatively area-specific datasets, it is not clear how the trained algorithms perform in other geographic locations.
- Although there is a study dedicated to completing deep learning output with the help of a GIS plugin, the constructed cadastral boundaries were not used to improve the predictions made by the deep learning model.
- There is no large-scale research executed on the physical properties of cadastral boundaries. Studies showed substantial overlap between cadastral boundaries and physical objects, but these studies are all focused on relatively small geographical areas.

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BIOGRAPHICAL NOTES

Jeroen Grift has been working as a GIS developer at Kadaster since 2018. In 2022 he started a PhD at the Faculty of Geo-Information Science and Earth Observation (ITC) of the University of Twente. His PhD is focused on applying deep learning techniques for cadastral mapping purposes. Within Kadaster, he works as a GIS developer for the project Kadastrale Kaart Next. In this project, millions of field sketches will be vectorized and positioned with the help of deep learning. Before, he worked at CycloMedia as a GIS specialist and studied Landscape History (MA) at the University of Groningen and Geomatics (MSc) at the University of Gävle.

Claudio Persello is an adjunct professor at the Faculty of Geo-Information Science and Earth Observation (ITC) of the University of Twente. He received the Laurea (BSc) and Laurea Specialistica (MSc) degrees in telecommunications engineering and the PhD degree in communication and information technologies from the University of Trento, Trento, Italy, in 2003, 2005, and 2010, respectively. Before joining ITC in 2014, he was a Marie Curie research fellow, conducting research activity at the Max Planck Institute for Intelligent Systems and the Remote Sensing Laboratory of the University of Trento. His main research interests are in the context of machine learning and deep learning for information extraction from remotely sensed images and geospatial data. The activity includes investigating and developing dedicated deep learning techniques for various remote sensing sensor data and multiple applications, focusing on societal and environmental challenges. He is particularly interested in combining deep learning and earth observation to address and monitor the progress towards the sustainable development goals.

Mila Koeva is working as an associate professor at the Faculty of Geo-Information Science and Earth Observation (ITC) of the University of Twente, the Netherlands, in support of 3D urban modeling (digital twinning) and cadastral applications. Her photogrammetry and remote sensing expertise includes image data acquisition, processing techniques (satellite, aerial, and UAVs), and automatic feature extraction for cadastral mapping. She has been working on geospatial data fusion using innovative methods to support resource management and decision-making for cadastral mapping and urban planning.

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