DETECTION OF POTENTIAL MICRO LAND GRABBING IN THE NETHERLANDS USING DEEP LEARNING

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SHAN SHI Enschede, The Netherlands, June, 2020

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation. Specialization: Land Administration

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ABSTRACT

In the Netherlands, the behaviour of residents grabbing small pieces of municipal land has attracted the attention of the government for the past ten years. Currently, the Dutch government uses traditional visual inspection methods to find the potential micro land grabbing cases from aerial images. In the long run, this traditional approach is costly, time and labour intensive. To date, this problem has received limited attention. There is some research focusing on the causes and characteristics of its occurrence. Our research aims to propose a novel and efficient method to identify the potential micro land grabbing cases in a complex urban area. We present an automated method, which involves deep convolutional network but also image analysis.

This automated method addressing a semantic segmentation problem in an endeavour to distinguish "potential micro land grabbing (PMLG)" pixels from "Non-PMLG" pixels, respectively. However, the visual cues to define a PMLG case directly from the image is too complicated for machine to learn as it also involves land tenure situation. Specifically, the first part of this method develops a SegNet model with overall F-score higher than 0.8. SegNet model extracts land cover features from the imagery automatically and then shows the output in an inference classified map, where each pixel is well predicted into different land cover types, such as buildings, gardens, water area, roads, etc. Based on the outputs created using deep learning, image analysis is performed with the help of official land right information provided by Kadaster. The output of the calculation classifies each pixel into "PMLG" or "Non-PMLG", which is the final result of the proposed method.

The method is also compared with the result of traditional visual inspection in Dutch cadastre. The result from the comparison shows that the proposed automated method finds most of the PMLG cases also outlined from the Kadaster and finds some additional. The results are shown false positive and false negative, respectively. An average of 0.20 precision and 0.54 recall has been achieved. For the IoU score, the class PMLG is 0.16 and Non-PMLG is 0.98, on average 0.57. This research concludes that the proposed automated method is a novel, effective and efficient method that can speed up the currently used from the Kadaster method in identifying PMLG in the Netherlands.

KEYWORDS: micro land grabbing, semantic segmentation, deep learning, fully convolutional network

ACKNOWLEDGEMENTS

Foremost, I would like to express my sincere gratitude to my supervisors, Dr. Mila Koeva and Dr. Claudio Persello, for your continuous supports, for your motivation, enthusiasm, patience and immense knowledge. Thanks Mila for replying to emails and revising papers even on weekends, arranging our regular video conferences. Thanks Claudio for answering all the questions about deep learning and providing helpful literatures. Your guidance helped me in all the time. I could not imagine having better supervisors for my master research.

My sincere gratitude also goes to Dr. Paul van Asperen for your help during the proposal phase. Thanks Dr. Jaap Zevenbergen for providing the valuable reference papers; Thanks to Dimo for organizing the online coffee time during the quarantine. To ITC Excellence Scholarship Programme, thanks for providing me the opportunity to pursuit Master degree in the Netherlands.

Special thanks go to the Kadaster for providing me the internship. Working in the GEC-Kadaster is a fantastic experience. I am immensely obliged to Vincent for your elevating inspirations, encouraging guidance and kind supervision in the completion of my research. I am deeply grateful to the Diede's help in technical support and Jacco's help in preparing internship documents and the background introduction.

Finally, I would like to thanks my parents Shi jianshuang and Lu lizhi for giving birth to me. For my dear elder sister, Sol, thank you for forcing me to take the TOEFL test and helping me prepare documents of studying abroad. Thanks the considerable jetlag between GMT+1(NL) and GMT-7(USA), which is convenient to have your video companion for my every struggling writing night. Every time I made my life-changing decision, you are always there for me. I love you and will always do.

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LIST OF ABBREVIATIONS

English:

PMLG	Potential Micro Land Grabbing
LULC	Land Use and Land Cover
GNSS	Global Navigation Satellite System
RMSE	Root Mean Square Error
Pb	Probability of Boundary
gPb	Global Probability of Boundary
BEL	Boosted Edge Learning
CNN	Convolutional Neural Network
FCN	Fully Convolutional Network
MRF	Markov Random Field
CRF	Conditional Random Field
DKs	Dilated kernels
SVM	Support Vector Machine
VHR	Very High Resolution
TR	Training Tile
TS	Testing Tile
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
Dutch:	

LKILandmeetkundig en Kartografisch InformatiesysteemPDOKPublieke Dienstverlening Op de KaartBGTDe Basisregistratie Grootschalige TopografieLVBGTLandelijke Voorziening De Basisregistratie Grootschalige TopografieBAGBasisregistratie Adressen en Gebouwen

1. INTRODUCTION

1.1. Background and justification

The land is a finite resource, while human demands on them are not (FAO, 2011). As the repercussion of this imbalanced supply and demand, thousands of land issues have arisen for centuries. Among those issues, the land grabbing phenomenon has aroused a long-standing and wide-ranging scientific debate about its alarming spread and its significant influences on social, political, economic, and environmental issues (Carroccio, Crescimanno, Galati, & Tulone, 2016). Despite the global reach on land grabbing, there is no definition that fully captures this issue (Baker-Smith & Szocs-Boruss, 2016). Zoomers (2010) defines land grabbing as "border-crossing land transactions that are implemented by transnational corporations or initiated by foreign governments in a large-scale." However, land grabbing is hardly anything new and can also happen in small-scale or initiated by individuals. While "big" cases of land grabbing in underdeveloped and developing countries are spread out in the media and attract most of the public attention, land grabbing taking place at the micro-scale, like in a community, is also worthy of attention. Under this circumstance, "grabber", usually farmers or inhabitants, with private land adjacent to the public land encroach by gradually moving the physical boundary, incorporating the public land into their own holdings, and using it as their own to the exclusion of others (Robinson, 2004). Thus, "micro land grabbing" is defined.

In China, a common case is that public green area in front of and behind inhabitants' house is partly transformed to unlawful vegetable plots in urban communities (Jin, Jiahong, Wenzhong, & Xiaofeng, 2016). In India, the raised platforms outside the houses have been extended over the years and now take most of the alley (Robinson, 2004). Some Indian epitomized the philosophy of "micro land grabbing" when they find empty land on parcel borders, advancing a few feet noiselessly. The same case happened in Bhutan (Karma Choden Tshering, 2018), along with the increasing number of households within a parcel, where the size of the plot is not sufficient to sustain a family, people gradually encroached the vacant state lands adjacent to their registered land.

Though this land encroachment is rarely considered to be a problem in developed countries as they have a more comprehensive management system, it does happen. In Ontario, the extension of residential lawns and gardens are extraordinarily serious. They lead to a long-term loss on the public forest area and put potential risk to the future living environment (McWilliam, Brown, Eagles, & Seasons, 2015). In Australia, the Melbourne suburban council declared that they lost 428 square meters of public land due to adjacent inhabitants fenced small pieces of public land to exclude the public management (O'Connor, 2014).

In response to this unsatisfactory behaviour, many countries or municipalities introduced several administrative ordinances and related penalties. For instance, in Ontario, Canada, governments have policies that seek to protect designated green infrastructure from the negative impacts of residents' yard extension encroachment (McWilliam et al., 2015). And in East America, the fine of public land grabbing might add up to \$2,000 or even potential jail time (Sadlouskos, 2013). However, those are passive administrative actions.

Only when the case is discovered, relevant punishment will be implemented. As for the undiscovered cases, they still have potential risks to traffic safety and the maintenance of cables and pipelines (Hoops, 2018). Micro land grabbing case also threatens the reliability of publicly available information and land transaction since provided data are not that accurate anymore. Therefore, it is imperative for the government to investigate the micro land grabbing phenomenon proactively.

A common way to detect "micro land grabbing" cases is by comparing the physical land-use situation and the official cadastral dataset directly. It was for property taxation that Napoleon introduced the cadastre in the Netherlands in 1811. After his downfall, cadastre continued. At that time, cadastral data was collected by land surveyors, who visited all individual landowners to check the ownership, usage, and area, etc., cooperating with the local major. Afterwards, changes in the cadastral situation were documented by "hulpkaarten" (supportive maps). On these documents, the changes were indicated by field sketches, including the survey data of the new boundaries (Soffers, 2017). Based on all the historical cadastral information, a digital cadastral database was developed, called "cartografisch gegevensbestand", currently known as LKI. Currently, digital cadastral maps are freely available at the PDOK platform¹. Generally, the PDOK provides an up-to-date overview of the cadastral situation of the whole country. However, the updating of the cadastral data is based on changes in the legal status. Moreover, updates of the cadastral boundaries appeared by only "verificatieposten" (verification²) and "splitsen" (splits³), where new spatial units are created (Soffers, 2017). A particular case is when Kadaster (Cadastre, Land Registry and Mapping Agency of the Netherlands) receive specific requests from stakeholders to visualize or re-demarcate an already determined boundary in the field, called boundary reconstruction. The fact is that the existing cadastral maps do not provide up-to-date information on all parcel boundaries, some boundaries have not been updated since the foundation of the Kadaster as the user did not report it.

Over time, four different survey techniques were applied in the Netherlands to measure boundaries, GNSS, tachymeter, measuring tape and photogrammetry (Soffers, 2017). The first three techniques are called direct methods, and are much more popular for measuring new boundaries and boundary reconstruction. Photogrammetry is defined as an indirect method and is mainly used for topographic map creation and updating (Soffers, 2017). Cay, Iscan, and Durduran (2004) concluded that the utilization of the satellite images is 99% cheaper than the classical map production method and saves 77% of the working time. Nowadays, a more cost-effective and flexible methodology is utilized with the use of aerial photo interpretation, and increasing attention is given to the utilization of images acquired from unmanned aerial vehicles (UAV) (Koeva et al., 2020). Aerial images, with relatively high resolution and traceability in a timeline, have significant contributions to meeting most of the land projects' prioritized needs (Stöcker et al., 2019). Koeva, Muneza, Gavaert, Gerke and Nex (2018) justified the potentiality of UAV images in providing information with a very high temporal and spatial resolution at a low cost. They produced high-quality orthophotos with an accuracy of RMSE of 8.8 cm that can be applied in cadastral map creation and updating. Therefore, aerial imagery can be considered a suitable solution for delineation of visible cadastral boundaries.

¹ <u>https://www.pdok.nl/</u>

² Verificatieposten: one party transfers a part of its parcel to another party.

³Splitsen: this is mainly done to exclude another part from influence on the position of a new boundary.

With the development of technology, automatic and semi-automatic boundary detection techniques are being explored by more and more researchers. Edge detection, regarding edges as sharp discontinuities in brightness and colour (Wassie, Koeva, Bennett, & Lemmen, 2018), provides a basis for object detection in image analysis. By reviewing all proposed methods of edge detection, this work can be divided into few categories such as a) Traditional detection operator, which includes Sobel and Canny detector (Wassie et al., 2018); b) Manually designed features like Statistical Edges (Davies, 2018), Pb and gPb (Crommelinck et al., 2016) and c) Learning-based methods that remain reliant on features of human design, such as BEL, Multiscale, Sketch Tokens, and Structured Edges (Persello & Stein, 2017). Additionally, there has been a recent wave of using deep learning method, especially Convolutional Neural Networks that emphasize the importance of hierarchical feature learning, including N4-Fields, Fully Convolutional Networks and Holistically-nested edge detection (Crommelinck, 2019).

1.2. Research problem

Land grabbing in a small scale is not a new case in the Netherlands. In 2012, there was a news item which published detailed number of situations of micro land grabbing (Helvoirt, 2012). In November 2018, de Volkskrant, one of the Dutch daily morning newspaper, reported news about land grabbing by citizens, taking small parts of municipal land that based on the research of Björn Hoops ("Landjepik kost gemeenten miljoenen", 2018). In Hoops' study (2017), 600,000 cases were estimated, and more than one million residents have been involved in the illegal use of small parcels owned by the municipality. It is evident that people are using municipal land to extend their gardens, driveways or even houses. To solve this problem, Kadaster launched a project called "Snippergroen" (Municipal greenery plots, which are generally of small size and are not part of the main green structure or municipal infrastructure.). Kadaster provides custom-made services for residents by delivering a map on a case-by-case basis, indicating the situation found, including surface area and the possible user with the help of aerial photos, topographic maps, register data, and cadastral indications. This inventory supports residents in the decision to buy, rent or return the grabbed land to the municipality. However, this approach involves quite time-consuming.

From the perspective of academic research, the analysis of land grabbing that happened on the microscale level is still at the initial stage. Limited literature inspected "micro land encroachment over public land" in the content of the Netherlands. Moreover, deep learning, as the most popular approach in image analysis, has achieved great success in building or roof detection, even within the Kadaster. But very limited researches are using deep learning in cadastral information detection, especially in the urban areas of a developed country where building density is much higher than in rural areas. Taking the above challenges and opportunities into consideration, it is of interest to investigate innovative, cost- and time-efficient method to extract potential illegally used land.

Therefore, this research attempts to extract the land utilized in reality while contradicts the official cadastral data, in other words, classifying the land-use situation into potential micro land grabbing or no potential micro land grabbing cases. Also, this research will conduce to demonstrate the effectiveness of deep learning networks in learning discriminative land-related features and its superiority to the traditional methods. Further, this research tries to illustrate the possibility and feasibility of using the automatic method for the Netherlands governments to understand the micro land grabbing phenomenon better.

1.3. Research objectives and questions

1.3.1. General objectives

The general objective of this study is to detect potential micro land grabbing in the Netherlands from aerial images using deep convolutional neural networks.

1.3.2. Specific objectives

Objective 1: To identify the current methods for micro land grabbing detection in the Netherlands.

Objective 2: To develop a deep learning algorithm for detecting potential micro land grabbing cases and thus monitoring the development of micro land grabbing in the Netherlands.

Objective 3: To evaluate the results of the proposed method and compare it with the traditional method applied in the Kadaster.

1.3.3. Research questions

Objective 1:

- 1. What methods are being used for detecting micro land grabbing cases in the Netherlands currently?
- 2. What issues are related with detecting micro land grabbing in the Netherlands?

Objective 2:

- 1. Which deep learning network architecture is appropriate for detecting potential micro land grabbing cases?
- 2. What geospatial data are needed to detect potential cases of micro land grabbing?
- 3. How to design the training and testing data?
- 4. How to distinguish the potential micro land grabbing cases by using the deep convolutional network? Objective 3:
- 1. What is the reliability of the proposed method in detecting potential micro land grabbing?
- 2. What are the comparing results of the proposed method and Kadaster current method?

1.4. Conceptual framework

With the overview of the topic introduction and the research problem described in the context of the Netherlands, three general frameworks for solving the micro land grabbing problem were found, legal framework, institutional framework and spatial framework. In the content of this research, the focus is on the spatial framework. The conceptual diagram shown as Figure.1.

Potential micro land grabbing detection involves the physical land use information, official cadastral data and appropriate technique. To ameliorate this realistic problem, spatial framework designed in this research should follow some key principles. To be specific, from the aspect of case detection sources, aerial images should be used rather than field surveys; in terms of the detection technique, deep learning method selected for its distinct contribution in providing a sustainable opportunity of land cover land use updating and upgrading.



Figure 1: The conceptual map of potential micro land grabbing from aerial imagery using deep learning.

1.5. Thesis structure

The structure of this thesis is organized as following:

Chapter 1. Introduction

This chapter gives the background introduction of the research, clarifying what is the research problem, objectives and questions. The main concepts and the internal relationships are all indicated in a conceptual framework.

Chapter 2. Literature review

The definition of parcel boundary in general and its specific situation in the Netherlands are reviewed. Besides, the state-of-the-art semantic segmentation techniques and source of the data are also reviewed in this chapter.

Chapter 3. Methodology

A flowchart of the research methodology and the study areas, followed by a detailed description of different data, data pre-processing and methods for accuracy assessment.

Chapter 4. Implementation and results analysis

This chapter first describes the current method used in Kadaster to find potential micro land grabbing cases. Then, the experimental analysis using the proposed method. The design of each experiment and the results are presented in the sequence of land use land cover classification model and hyper-parameter tuning, potential micro land grabbing detection model and model fine-tuning, accuracy assessment. The results of alternative approaches are also described and the final comparison in this chapter.

Chapter 5. Discussion

Firstly, an elaborate discussion of the obtained results presents. Then, this chapter critically discusses the limitation of this research. The ethical consideration discussed at the end of the chapter.

Chapter 6. Conclusions and recommendations

This chapter closes the thesis with concluding remarks of the whole research, also making suggestions for future improvement.

2. LITERATURE REVIEW

2.1. Physical, legal and cadastral parcel boundary

Geometrically, parcel boundary can either be a line or polygon feature. A physical boundary, such as a wall, a fence, or a hedge, represents a spatial unit's location and spatial extent in the terrain, a ground truth data (Vos, 2015). It can be of assistance to stabilize the location of the boundaries and the shape of the plot. However, the physical boundary is not always a decisive legal fact. In a legal sense, Zevenbergen (2015) defines a cadastral boundary as a discontinuity line which separates the land interests of two parties, emphasizing not only the geometric features but also the exclusiveness of property right. In this research, the cadastral boundary is the official registered geometric data collected from land surveyors working in the Netherlands. This is a fixed parcel boundary which complies with the description in the notary deed of the land transaction.

Essentially, only in an ideal situation the physical boundary is also the cadastral and legal boundary. In the Netherlands, a possible case is that a part of one's parcel has been possessed by another for many years and as a result land ownership has been shifted (cases dependent and called "verjaringstermijn"). Therefore, as long as the prescription period has not been elapsed, the physical boundary can never be consistent with the legal boundary. Only after the elapsing of the prescription period, the physical boundaries coincide with the legal boundary. However, irrespective of the elapsing of the prescription period, the physical – and possibly also legal – boundary has a difference with the official cadastral boundary data. It is only after the prescription approved by certain legal procedures has been recorded under the witness of a notary and registered into a cadastral system, that the cadastral boundary can be brought in compliance with the legal boundary (Vos, 2015).

Cadastral boundaries can be divided into two categories, fixed or general. A fixed boundary refers to the precise line of the parcel, determined by legal surveys and expressed mathematically by distances or by coordinates (Bogaerts & Zevenbergen, 2001). A general boundary usually coincides with visible topographic features (Williamson, Enemark, Wallace, & Rajabifard, 2010). Comparing to the fixed boundary, general boundary extraction usually can save more investments in advanced-survey instruments and time, as it requires less standardized surveying procedures. Though a fixed boundary provides parties with confidence in the clarification of a property, a general boundary still guarantees the reliability of data and has strength in affordability, systematic large scale approach and sustainability. In the content of this research, both general and fixed boundary are considered.

2.2. Land use and land cover

According to the FAO, Land use is characterized by "the arrangements, activities and inputs by people to produce, change or maintain a certain land cover type". Distinguishing from the land cover which refers to the biophysical properties of earth surface, land use more concerns the usability of land by human activities. Human activities use land for various purposes including entertainment, settlement, food, public administration, etc. This results in land use for commercial, residential, agricultural and governmental activities. Moreover, land uses varies greatly between the urban and rural area owing to the population density and social-economic developments (Mengmeng Li, urban land use extraction from VHR RS image,

2017). However, we still consider the help of land cover visual cues, which facilitates the classification of green, roads and water bodies in the semantic segmentation.

Land use and land cover information is essential to understand the interaction between humans and the environment across different spatial and temporal scales (Muller and Munoroe, 2014). It is of importance for land management planners when analysing the evolution of human-environment interaction when solving realistic land issues. Thus, it helps to develop solutions for sustainable use of these limited natural resources.

This study focuses on land in urban areas where the size of land grabbing cases usually is at the micro-level, meeting the current needs of the governments' interests at the same time. To be specific, the land in the content of this research can be divided into the plots that is used for private citizens, like residential area and its garden, or the land that is part of public infrastructure, like roads, water, etc. Well extracted land use and land cover information facilitate the process of finding potential micro land grabbing cases.

2.3. Semantic segmentation techniques

To our knowledge, the terminology "semantic segmentation" can be dated back to 1970s (Ohta, Kanade, & Sakai, 1978) and it was equivalent to the image segmentation but required segmented areas must be "semantically meaningful" (Yu et al., 2018). Nowadays, semantic segmentation is defined as the process of determining class labels for each pixel and localizing predicted pixels at the original image pixel resolution (Yu et al., 2018). Comparing to the image segmentation, semantic segmentation is performed at the pixel-level.

The breaking point for semantic segmentation research is the founding of FCNs (Ulku & Akagunduz, 2019). Before the FCNs, traditional image segmentation methods include Markov Random Fields (MRF) (Kindermann & Snell, 1980), Conditional Random Fields (CRF) (Shafiee, Wong, & Fieguth, 2017) or forestbased (also referred to as 'holistic') methods. These contextual models, also called graphical model, aim to find an inference result by investigating the dependencies between neighbouring pixels (Kohli, Osokin, & Jegelka, 2013). Currently, the aforementioned graphical models are no longer preferred as semantic segmentation methods for the reason that the deep neural networks are much more powerful in extracting or learning the local feature (Fulkerson, Vedaldi, & Soatto, 2010). Nevertheless, model like CRFs is popular in postprocessing. They are used as refinement layers with the purpose of improving the semantic segmentation performance as they have better performance in extracting global context information (Ulku & Akagunduz, 2019).

As we mentioned before, the most recent wave of semantic segmentation approaches is learning-based, which has shown good capability in learning high hierarchical feature concepts (Crommelinck, Koeva, Yang, & Vosselman, 2019). For decades, convolutional machine-learning techniques have challenges in constructing a satisfying representation or feature vector of raw data for computer understanding. Inspired by the information processing procedure in the human brain, the deep learning method takes raw input as a starting point and transforms the representation at one layer into a representation at a higher and more abstract layer (Lecun, Bengio, & Hinton, 2015). This multilayer transformation architecture improves the selectivity and the invariance of the representation. Considering the drawback of other deep network typologies, like the expansive parameters' number in Deep Neural Networks and Recurrent Neural

network's inability in temporal analysis, Convolutional Neural Networks gain more popularity for they are easier to train and fewer parameters required ("Convolutional Neural Network," 2013). Tremendous breakthroughs in face detection, handwritten recognition, deep geo-localization, and robotics have been achieved by using CNNs. Two layers are included in traditional CNNs, convolutional layers to extract spatial-contextual features and fully-connected layers to learn the classification rules, respectively (Persello & Stein, 2017). Later, Jonathan (2015) promoted a "Fully convolutional network (FCN)" where the fully connected layer in the contemporary CNNs was substituted by convolutional layer and gain a capability to have a fine prediction at every pixel. (Figure 2) Instead of giving an input image just one global predicted label, FCN gives a detailed label to each pixel in the image. In Persello and Stein's study in Dar es Salaam's informal settlement detection (2017), FCN with dilated kernels (FCN-DKs) obtained 86.09% overall accuracy which is much higher than the Support-vector machine (SVM) method and Patch-based CNN.



Figure 2: The illustration of FCN learns to make dense predictions for pixel-wise tasks.

FCNs for land use change detection was investigated by Ruoyun (2019) for Bangalore based on very high resolution images. The architecture of FCN in her work was modified from the FCN-DKs (Liu et al., 2019). It consists of 7 convolutional layers interleaved by batch normalization and Leaky Rectified Linear Units (Leaky ReLU), one more convolutional layer for classification, a dropout layer for alleviating the occurrence of overfitting and a SoftMax layer to generate classification result.

2.4. Semantic segmentation sources

Despite the various approaches in semantic segmentation, challenges are also encountered due to the variety of input information. Basically, there are two sources of information that can be used for potential micro land grabbing detection. The first can be, point cloud data from Airborne Laser Scanning (ALS). It has the advantage of having highly accurate height information. Many researches have already been done on feature extraction from ALS in the domain of urban planning and land administration. Examples include cadastral boundary extraction (Luo, Bennett, Koeva, & Lemmen, 2017), land cover classification (Enemark, McLaren, & Lemmen, 2016), land abandonment exploration (Janus & Bozek, 2018), building detection (Tomljenovic, Tiede, & Blaschke, 2016) and traffic islands modelling (Zhou & Stein, 2013). In Luo's search (Luo, Bennett,

Koeva, & Quadros, 2016), a promising result of 80% completeness, 60% correctness on parcel boundaries extraction was achieved by using a LiDAR data with a point density of 9.47 p/m2. Another approach of feature detection is image-based, which is conventional has also a great potential. In the past ten years, increasing popularity on boundary detection using UAVs and RS imagery. Xue's is using UAV images in the content of Busogo and Muhoza at a resolution of 0.02m, very high resolution images, which provide detailed ground information for cadastral boundary estimation (Xia et al., 2019).

Both images mentioned above are very high resolution (VHR), characterized by spatial resolution at or below 1m. VHR image utilization is the most progressive domain of current remote sensing researches. The majority of the equipment that captured those images carries the most modern systems with great flexibility and capability to collect data according to the very concrete requests. They are widely used in detailed mapping, 3D city modelling and precision agriculture. In this research, very high-resolution imagery is required as it enables the computer to identify the physical characteristics of visible parcel boundary and LULC features in images. Moreover, here micro land grabbing activity alludes to the private landholders encroach a few square meters of municipalities' lands.

2.5. Summary

This chapter reviewed the key concepts and prior researches that relate to the potential micro land grabbing detection. By introducing the physical, legal and cadastral parcel boundaries situation in the Netherlands, we illustrate the research background again. Instead of comparing physical and cadastral boundaries, the potential micro land grabbing is seen as the contradictions between physical land use land cover situation and officially registered land use land cover information in the cadastral data. Moreover, we clarified the efficiency of using fully convolutional networks in semantic segmentation. Hence, FCN is determined to be applied for potential micro land grabbing detection in our research. Considering the research objects are those cases with small areas, We select VHR imagery as the input data of the research.

3. METHODOLOGY

3.1. Study area

There are potential micro land grabbing cases everywhere in the Netherlands (Hoops, 2018). Considering the availability of remote sensing imagery and the integrity of related supporting data, two municipalities were selected as case-study areas, Zwolle and Zoetermeer. Furthermore, these two different datasets help not only in enlarging the training data size, but also enriching the diversity of classifiers' characteristic in the RGB image. A general view of the study area, along with the geographic information, is given below.



Figure 3: An overview of the study area, Zoetermeer, and Zwolle.

The municipality of Zwolle is the capital of the province of Overijssel. Zwolle is a hub in the national highway network, and also the gateway to the northern Netherlands. One of the eight Kadaster offices is located in the Zwolle, providing diverse land services for the eastern Netherlands. Given the benefits from the Kadaster's powerful data supplementation and technical supports, Zwolle is chosen as one of the study

areas. In 2019, the project "Snippergroen" just finished its task to find the potential micro land grabbing cases manually. This newly completed project provides us with comparable data for our proposed method and the final research results. Therefore, to ensure data accessibility and comparability, we chose also Zoetermeer as the research area.

3.2. Overall methodology

The flowchart in Figure 4 shows the overall methodology of this research. Blocks in different colors represent preliminary work, including related information and data collection, mid-term implementation, and final result's evaluation and comparison, which correspond to the three main research objectives.

From the preliminary literature review fully convolutional network to detect potential micro land grabbing cases was selected to be used. Moreover, to investigate the current methods used in the Kadaster in detecting PMLG cases, interviews were done in addition.

It is worth noting that we repeatedly use the deep learning models in an orderly manner, first to perform land use land cover (LULC) classification and then potential micro land grabbing (PMLG) detection. Instead of directly detecting the physical boundaries, the grouped deep learning models gain inference classified land map firstly, then the inference result in LULC classification is used for detecting PMLG. Therefore, the training and testing tiles in PMLG detection are actually split from LULC classification's testing tiles. In the PMLG detection process, public or private land information from the Kadaster database involved.

The reason for using a grouped deep learning model is that it is challenging to detect parcel boundary directly in complex urban environments, where the density of objects and complexity of the texture in VHR images are both high. Also, it is not difficult to imagine that the total number of non-boundary pixels might be millions of times the number of boundary pixels when we are performing the binary classification to distinguish boundary pixels with non-boundary pixels. This massive imbalance in the sample data, therefore, inevitably leads to an unsatisfactory training result. Taking into account such results, we choose the indirect method.

In the end, detected PMLG results using the proposed deep learning model are evaluated and compared with the results that are obtained in the Kadaster.



Figure 4: The overall methodology.

3.3. Data and data pre-processing

This research contains both primary data and secondary data. The project manager in the Kadaster is interviewed to obtain the required background information regarding micro land grabbing cases (land encroachment). Secondary data mainly includes the available aerial images, information from different literature, documents from the Kadaster, and pieces of papers found to be relevant for the theme of this study obtained from various sources.

3.3.1. Very high-resolution imagery

I. Zwolle

The VHR imagery covered the urban area of Zwolle and was captured in 2016. They were provided by Kadaster from their database. The images have three bands (RGB) and spatial resolution in 0.1 m. Eighteen tiles are randomly selected for training (TR) (Figure 5). The other eight tiles are selected for testing because Kadaster data indicating that there are high suspicious PMLG cases. In total, twenty-six tiles of 2500×2500 pixels were picked in this study site for the experimental analysis.



Figure 5: The VHR imagery of Zwolle. Training and testing tile are indicated by the blue and yellow squares, respectively.

II. Zoetermeer

The VHR imagery in this study site was acquired for the "Snippergroen" project in 2018. These images also have three bands (RGB) with spatial resolution in 0.1 m. Eighteen tiles that cover almost the whole high suspicious PMLG case in the city center were picked. Each tile has 2560×2560 pixels. These eighteen tiles were equally split into training and testing tiles, nine for training and nine for testing (Figure 6).



Figure 6: The VHR imagery of Zoetermeer. Training and testing tile are indicated by the blue and yellow squares, respectively.

By combining data from these two research areas, we got the third data. Hence, there are three groups of experiments in the LULC classification. The first and second groups used Zwolle and Zoetermeer images, respectively, while the input aerial images of the third group combine the Zwolle's and Zoetermeer's.

3.3.2. Supportive spatial data

I. Land cover and land use reference data

Kadaster geodata-center contains tremendous geo-informatic data. Among them, Basic Registration of Large-scale Topography (BGT) provides the updated graphic representations of features that appear on the land of the Netherlands. Nowadays, BGT is increasingly being delivered and is becoming available in the National Provision (LVBGT). LVBGT contains diverse features, like roads, bridges, buildings, urban development, railways, waters, names of places and geographic features, administrative boundaries, state and international borders, reserves, etc. The building information in the LVBGT also called BAG. Taking into account the time required for model

training and our research purposes, we merge some features into one land category. In the end, five categories selected (Table 1).

LULC Classes	Pixel Value
Gardens	1
Roads	2
PublicGreen	3
Water	4
Buildings	5

Table 1: The attributes of land use land cover reference data.

II. Public or private map

Public or private (Public/Private) map comes from both LVBGT and also from the output of project "Snippergroen". This data reflects a relatively updated land right status. It clarifies where are the public land and where is the private land. Thus, it is a binary dataset, with pixel value either one or two (Table 2).

Registered Land Right	Pixel Value
Public	1
Private	2

Table 2: The attributes of public/private map data.

III. Manually digitized potential micro land grabbing data

This data is provided by the project manager in the Kadaster and finished project "Sinppergroen" for the study areas. Since this is private data and has specific owner information, it is un-retrievable in any open portal. From 2011, Kadaster started systematically to work on MLG using as a base this digital geographic data, providing the location, size of the cases, also the information of stakeholders. Like the registered land right data, our output is also binary data. Table 3 gives data attributes.

Land Use Situation	Pixel Value
PMLG	1
Non-PMLG	2

Table 3: The attributes of manually digitized PMLG data.

Therefore, for each tile, there are four corresponding data attached, here we give an example of one tile in the study area Zwolle, TS15 in Figure 7. In the first procedure, LULC classification, we only use the RGB imagery, the LULC reference data. In an endeavour to detect potential micro land grabbing cases, we need the official cadastral data, therefore the registered land right data evolved. In PMLG detection, inference LULC classification result together with the land right provides the raw information. Hence, two one-dimensional data become a two-dimensional data.



Figure 7: Spatial data of Testing tile 15 in Zwolle, a)RGB imagery; b)Manually digitized PMLG data; c)LULC reference data; d)Registered land right data.

3.3.3. Interview

To investigate the current method used for detecting potential micro land grabbing cases in the Netherlands, we need to interview the professionals who are familiar with the whole procedures and have rich experiences in conducting the related data. As we mentioned before, there is limited research on the topic of micro land grabbing and the research topic is with high level of sensitivity, so it is impossible to figure out the current situation of PMLG. Conducting expert interviews provides us detail and reliable information about how Kadaster finds the potential micro land grabbing cases, what kind of data and software do they use, the time and energy they spend, and their self-evaluation and outlook, etc.

3.4. Deep learning model set up

As we showed in the overall methodology, experimental analysis can be divided into two steps. The first step aiming to do the supervised multi-classes land cover classification, and it uses FCN-SegNet model with pre-trained VGG-16 weight. Figure 8 shows the specific architectures of SegNet. Since there are two study areas in this research, the LULC experiments can be divided further into three groups. The first group using only RGB imagery that covers Zwolle; the second group using imagery of Zoetermeer while the dataset in the third group combines the images of both Zwolle and Zoetermeer. Under the framework of PyTorch, the whole process was run on the Microsoft Azure virtual machine with NVIDIA Tesla 4×P40 GPU and 448 GiB memory.



Figure 8: The illustration of the SegNet architecture. (Source: Badrinarayanan, Kendall and Cipolla, 2017)

The second step is regarded as a binary classification task aiming to distinguish PMLG pixels with Non-PMLG pixels of input raster data. In order to keep the consistency of the research method, we still use FCN-SegNet model in this step. However, considering the truth that the complexity of input data has only two layers, we also adopt FCN-DKs network to find potential micro land grabbing cases. FCN-DKs (Figure 9) network uses the dilated kernel to enlarge the receptive field without downsizing the image dimensions but also performs efficient computation with lesser memory consumption. For the model training using FCN-DKs, the whole process was run on the Microsoft Azure virtual machine with NVIDIA Tesla 1× P40 GPU and 56 GiB memory.



Figure 9: The architecture of FCN-DK6 for Boundary Detection. (Source: Persello and Stein, 2017)

3.5. Accuracy assessment

In order to illustrate whether the output result meets the user's requirement and makes a comparison with other data, we need to assess the result's accuracy duly. With the development of geographic information, a professional guideline for evaluating the geographic data quality was introduced by the International Organization Standardization(2013). ISO defines geographic data quality in six elements, that is completeness, thematic accuracy, logical consistency, temporal quality, positional accuracy and usability. Each element contains a number of sub-elements, for example, completeness (commission and omission), logical consistency (conceptual, domain, format, topological), etc. In this research, the completeness and thematic accuracy gain more emphasis. By using these two elements, many confusion matrices can be designed to facilitate the evaluation of binary classification. Among them, precision-recall measures and the F-measure are the most commonly used (Crommelinck, 2019). In the PMLG detection, binary classification

is performed. In the PMLG result measurement, the positive refers to PMLG pixels and negative is Non-PMLG pixels. The predicted means the inference result of the deep learning model and "actual" is the pixels' label in the result that is obtained with the method of Kadaster. Furthermore, precision measures the ratio of correctly detected PMLG pixels to the total detected PMLG pixels. Recall, also called completeness, indicates the percentage of correctly detected PMLG pixels to the total PMLG pixels in the "actual" dataset. However, in the first step of this research, we implement multi-class classification task. Under this circumstance, it is meaningless to define the positive or negative classes as there are more than two classes. But we can still use the precision and recall to measure the result's accuracy. The combination of precision and recall is the F-measure. The interpretation of this evaluation matrix is shown in Figure 10.



Figure 10: The evaluation matrix for pixel-wise classification. (Adapted from: Xia et al., 2019)

Another popular evaluation metric is IoU, an intersection over union. In simple terms, it considers the overlap rate between the target window generated by the model and the original labelled window (Rosebrock, 2016). IoU will always be a value between zero and one. In general, the higher the IoU value, the better result. The significance of using IoU is it gives the similarities and differences of two datasets instead of categorizing pixels into positive or negative. Moreover, there is an internal connection between Precision-Recall-F-score matrix and IoU matrix. In the context of object segmentation, Jaccard introduced intersection as TP while union as the sum of TP, FP and FN (Pont-Tuset & Marques, 2016). Thus, IoU is defined as:

$$IoU = \frac{|TP|}{|TP|+|FN|+|FP|}$$

In this research, the intersection, also the true positive, represents those lands that inference as PMLG pixels in both deep learning method and Kadaster method. And the Union is the PMLG pixels in either the inference result of the proposed method or the result of Kadaster traditional method. In Figure 11, the "Detected box" represents the inference result of the proposed method in this article while "Object" is the PMLG result obtained from Kadaster's visual inspection.



Figure 11: The illustration of IoU metrics. (Source: Data Science Stack Exchange)

To make a comparison between the proposed method in this research and the Kadaster tool, another evaluation method is used adopted from the perspective of economics, which is cost-benefits analysis. In this content of research, the benefits relate to the accuracy of the final results. At the same time, the cost considers their processing time, computational risk and uncertainty, experts' level, and GPU power consumption.

3.6. Summary

This chapter represents the methodology to achieve the research specific objectives. The urban areas of two municipalities, Zwolle and Zoetermeer, are selected as study areas. Required geospatial data includes VHR aerial imagery that covered two selected study areas collected, the reference data of land use land cover and public/private map from Kadaster geodatabase. Comparative data is the potential micro land grabbing result that manually digitized by Kadaster. In total, forty-our tiles with the spatial resolution of 10cm are selected from two sites. In parallel with the conclusion of the current method for PMLG detection in the Netherlands, our proposed method uses two deep learning sections to detect the PMLG cases indirectly, one section is for LULC classification using SegNet and the other one is for PMLG detection using both SegNet and FCN-DKs. Two metrics, Precision-Recall and IoU, are selected as the basis for accuracy assessment and methods comparison.

4. IMPLEMENTATION AND RESULT

This chapter describes different experiments using the proposed deep learning model for obtaining LULC classification and detecting PMLG cases. Section 4.1 introduces the methods for PMLG detection in the Netherlands at current, while section 4.2 introduces the methods proposed by this article. In detail, section 4.2.1 shows the result of the experiment of LULC and 4.2.2 displays the result of PMLG cases detection. Considering the outcome of section above, section 4.2.3 gives an alternative method to gain a better research result.

4.1. The current method used in the Kadaster

The current method of PMLG detecting in the Netherlands is summarised based on the knowledge obtained from the expert interview and related literature review. As the government agency that manages geographic and cadastral information in the Netherlands, Kadaster has the responsibility to oversees the illegal land use cases. In the past decade, the project "snippergroen" has completed its discovery of unlawful land grabbing cases in many municipalities. In this research, a data engineer who has rich experiment in making PMLG data received interviews.

To find potential micro land grabbing cases, several data and software are used. Aerial imagery that reflects the physical reality provides the base map and the resolution requirement is usually 10cm, the threedimensional street view used to check the uncertainty case at the same time. Specifically, the 3D street view data are helpful to confirm further which cases are hidden in the image's shadow or below the trees or sheds. Furthermore, the street view data compensates for the obstacles caused by the low resolution of remote sensing images. In the Netherlands, the aerial image in winter is usually 25cm. In short, the combination of the two data helps to ensure the effectiveness of the work further. Usually, this work is done in Geomedia 2015, but ArcGIS Pro or even QGis will be used. In the specific data production process, the engineer confirms the geographic location of each parcel, one by one carefully, in the aerial image together with the simplified property records in the cadastral map. About the required labour (time), it is mostly dependent on the number of parcels that need to be checked. For an experienced engineer, they are able to check about 200-300 parcels in around an hour reliably. It also depends on the specific layout of the neighbourhoods and buildings. Considering that the coverage area of one tile in our research is $2500 \times 2500 \times 0.1$ m with an average of 205 buildings, we assume the Kadaster method almost takes an hour to process the same workload as one tile in our research.

Moreover, during the procedures of data making and analyzing, there are several findings accumulated which is also conducive to subsequent repetitive work. Those finding are concluded from the interview as well as the research of Hoop (2018), they are:

- I. There are neighbourhood layouts that positively prevent land grabbing from happening. For example, where gardens or houses are lined by the public sidewalks or streets, the sidewalk or street will typically not be grabbed;
- II. Neighbourhoods with older (say 1940 or before) buildings with larger front and backyards have higher rates of land grabbing;
- III. Detached or semi-detached buildings tend to have higher rates of land grabbing;
- IV. Micro land grabbing situation sometimes shows a tendency of group behaviour. In the same community, inhabitants often illegally use roughly the same size the municipal land for a similar purpose;

- V. Land grabbing is fairly uniquely tied to gardens and driveways. In city centres where gardens are a rarity and usually sort of patio's within a privately owned building block you won't find a lot of micro land grabbing cases;
- VI. Micro land grabbing cases rarely happened in the form of building expansion.

Concerning the accuracy of the data, it is not 100% correct. The likelihood of detection is around 90% to 95% guess. Of which, maybe 5% are false positives and others may be excluded for the reasons like visual omission and operational error. Hence, the need for field checking or a detailed inspection by the local municipalities or customers. Therefore, it is worth noting that the data "Public/Private map" labels the pixels into PMLG and Non-PMLG mentioned in the previous article and used later has error.

Though, in the current operation process, Kadaster is still using the traditional visual inspection method. But at the same time, they are also looking for more efficient and innovative approaches to speed up the research process and reduce the pressure on human labour. The department of spatial planning and advice seeks the opportunity to use the possibilities of artificial intelligence, machine learning and other new technologies to meet the needs of big geo-data analysis.

4.2. Deep learning for potential micro land grabbing detection

As we mentioned before, the process of detecting potential micro land grabbing using deep learning models is divided into two steps, LULC classification and PMLG detection.

4.2.1. LULC classification experiments and result

Before training, there are some hyper-parameter that must be set. Due to the large size of the training tile intercepted, 2500×2500 or 2560×2560, and the limited computing power of software and hardware, sliding window with size 256×256 and with stride 128 used in each experiment. With respect to the fine-tuning, varied basic learning rate (Base_lr), which controls the converging speed of the model, used, i.e., 0.1 or 0.01. Moreover, we also use the learning rate schedules to reduce the learning rate exponentially when the training epoch reached the designing number. Another changeable hyper-parameter is the different number of epochs, controlling the number of complete passes through the training dataset, 50 or 100 tested. In general, the strategy for hyper-parameter optimization follows the principle of a control experiment where only one different hyper-parameter exists comparing to other trials that used the same dataset. In total, there are eight experiments in LULC. Table 4 lists the record of conducted tuning experiments with their average F-score on testing tiles.

Experiment	Data	Base_lr	Epochs	Running	Average
No.				time(hr)	F-score
1	Zwolle	0.1	50	5.5	0.762
2	Zwolle	0.1	100	9.5	0.794
3	Zwolle	0.01	50	7.0	0.827
4	Zoetermeer	0.1	50	4.0	0.831
5	Zoetermeer	0.01	50	5.0	0.864
6	Zwolle & Zoetermeer	0.1	50	4.8	0.794
7	Zwolle & Zoetermeer	0.1	100	8.0	0.693
8	Zwolle & Zoetermeer	0.01	50	5.0	0.841

Table 4: Records of conducted tuning experiments and results.

Here, we are using the experiment six to eight as a representative to look at fine-tuning results. The obtained results are reported in Figure 12. From the figure, we can see that when the base learning rate set as 0.01, the model achieves a better result than 0.1 on test tiles in average F-score, precision, and recall. The purpose of experiment six and eight was to find the best number of training epochs. Comparing to training 100 times, setting training number of training epochs to 50 performs better with less computational time. Therefore, we can say that the model accuracy is not proportional to the number of epochs. In Figure 13, the learning curves experiment six and eight showed. We can see the loss of model in LULC keep decreasing in 50 epoch training while there is a clear moment where model loss stops dropping in 100 epoch training. To avoid the error of data overfitting and to reduce the computation time, we run the optimizer for 50 epochs for the following experiments, so as the PMLG detection step.



Figure 12: Classification accuracy of SegNet varying base learning rate and numbers of epoch.



Fig 13: The learning curve of SegNet varying number of epochs.

In Fig below, we give a visualization of the testing result produced by experiments attaining the highest F-score in each dataset, experiment 3, 5, and 8. The overall accuracy of these three experiments is 82.0%, 86.7%, and 83.6%, respectively.



Figure 14: a) The original RGB imagery; b) The LULC reference; c) Inference output of experiment 3; d) Inference output of experiment 8, in the study area of Zwolle.



Figure 15: a) The original RGB imagery; b) The LULC reference; c) Inference output of experiment 5; d) Inference output of experiment 8, in the study area of Zoetermeer.

The LULC results of SegNet in both testing tiles are visually satisfactory, but results are noisier when we use the combined datasets. In Figure 16, the F-score for each land cover class in each model tuning experiment is above 0.65. In experiment 3, 5, 8, where we obtain the highest average F-score for each dataset, F-score for each land cover classes approaching to 0.80. What stands out in Figure 16 is the F-score of class "Buildings", its F-score all close to 0.90. In general, we can say the inferencing result of buildings is close to the ground truth data. However, the class "Garden" has a relatively low F-score in each experiment. As we inspect the original imagery detailly, it is not difficult to find that "Garden" is a more general class comparing to others. We see mixed visual cues in the garden, including not only outdoor table, shed and vehicles, but also man paved road and green area which share the same features as the class "Roads" and "PublicGreen". This is a rather disappointing result of machine cannot provide a clear boundary between the garden and its around public green space, it is bound to affect significantly the accuracy of our identification of potential micro land grabbing cases in the next step. Therefore, we only used the inferencing result of experiment 3, 5, and 8 as the input data for PMLG detection because they achieved the highest average F-score along with the highest F-score of class "Garden".

Figure 16: The performance of eight experiments.

Deep learning model results in considerably high accuracy on land cover classification. Taking advantage of the available training data, supervised FCN-SegNet has the capability of learning to classify the different land cover, and inferencing each pixel in the testing tile into each class. Even if we combined the geographic data that covers different municipalities and acquired in different data, the deep learning model still is able to perform LULC classification without accuracy decreasing significantly. Therefore, it provides reliable input data for our next investigation.

4.2.2. PMLG detection experiments and result

To decide whether an area is potential micro land grabbing or not, logical thinking is whether the privateused land is bigger than their officially registered land and taking up the public land. Therefore, the research objective in this step is trying to find the differences between the physical land utilization situation with the official cadastral data automatically. Based on the result of section 4.2.1, the first layer of input data can be the result of classified land cover classes. Another essential information refers to the registered land right (LR), that is whether the land is registered as private-using or public-using. Hence, each pixel in the training tiles has, now, only two bands. The value of the first band range from one to five, represents different land cover classes and the other band describes the land right of this pixel, value "1" is public while "2" is private.

As we mentioned in the methodology, the data used in PMLG detection is split from the testing tile of LULC classification, only by doing so we gain the inference LULC result from deep learning model. Table 5 describes datasets used in PMLG detection, and Figure 17 gives an illustration of data used in the study area Zwolle, TS19 and TS11, respectively.

No.	Study area Training tiles		Testing tiles	
1	Zwolle	TS09, TS12, TS13, TS15, TS19	TS11, TS16, TS18	
2	Zoetermeer	TS01, TS07, TS11, TS15,TS17, TS21,TS23	TS03, TS09	
3	Zwolle & Zoetermeer	Combined above	Combined above	

Table 5: The training and testing tiles in each dataset for PMLG detection.

It worth noting that the reference data we use here, manually digitized PMLG cases from Kadaster as a3) and b3) in figure 22, is not 100% correct ground truth. The fact is that those cases discovered by Kadaster are highly suspected of micro land grabbing cases, with a likelihood of accuracy is around 90% to 95% as we concluded in the first section. They still need field checking or further confirmation. From the perspective of deep learning models, it relies on the kind of data with errors in learning process, which may result in the final result is not ideal.

Figure 17: Examples of training tile (a) and testing tile (b). a1)Band 1 of the input image, land cover classification result from experiment 3; a2)Band 2 of input image, land right- Public or Private; a3) PMLG cases manually made by Kadaster. Same as image b).

To perform case detection, the results of three LULC experiments that gains the highest F-score in each dataset are used as input for this second deep learning experimental analysis. In this procedure, we directly use the result from LULC_ex3, LULC_ex5 and LULC_ex8. Table 6 shows the detail of each experiment and the final F-score of PMLG on testing tiles via using FCN-DKs and Table 7 shows the details of using SegNet.

In both FCN-DKs and SegNet, we run the optimizers for 50 epochs with weight 1000.0 to 1.0 in the binary cross-entropy loss function. From the result of FCN-DKs, we can see the deeper the networks the longer running time. Although fine-tuning on the filter size and the neural network depth, all the final F-score Due to the extraordinary imbalance of the data ratio in the training samples, the testing results of these two deep learning models are poor, especially the results of FCN-DKs. However, we see a little improvement of F-score in SegNet experiment 11 when more training data loaded. In here, experiment 11 training image increases to 12, while experiment No.9 and No.10 have 5 and 7 images, respectively.

Experiment	Model	Input bands	Filter	Network	Running	F-score
No.			size	depth	time(min)	"PMLG"
1		$LULC_ex3 + LR$	3×3	6	42	0.009
2		$LULC_ex3 + LR$	3×3	9	80	0.001
3		$LULC_ex3 + LR$	5×5	6	80	0.008
4	FCN_DKs	$LULC_ex3 + LR$	5×5	9	200	0.012
5		$LULC_ex5 + LR$	3×3	6	62	0.004
6		LULC_ex5+ LR	3×3	9	120	0.008
7		LULC_ex5+ LR	5×5	6	118	0.011
8		LULC_ex5+ LR	5×5	9	296	0.008
	Table	6: Records of PMLG dete	ction experiment.	s using FCN-I	DKs.	
Experiment	Model	Input bands	Running	g F-sco	re A	verage
No.			time(min	ı) "PML	G" I	F-score
9		$LULC_ex3 + LR$	108	0.12		0.53
10	SegNet	$LULC_ex5 + LR$	120	0.10		0.52
11		LULC_ex8 + LR	120	0.15		0.57

Table 7: Records of PMLG detection experiments using SegNet.

The experiment No.1 to No.4 and No.9 using the first dataset. The experiment No.5 to No.8 and No.10 using the second dataset. The third dataset utilized in only experiment No.11. As we can learn from the figures 23, FCN-DKs model has poor performance in detecting the PMLG detection, the F-score in each experiment is quite low. In experiment No. 2 and No.4, where we enlarged the filter size in the convolutional layer, the F-score increased almost ten times. The experiments No.5 and No. 7 show the same improvement. However, when we try to increase the depth of the network, adding more convolutional layers, the F-score not always increased. In experiment No.1 and No. 2, the F-score of PMLG pixels decreased from 0.009 to 0.001. Comparing to the FCN-DKs, FCN-SegNet has better performance in PMLG detection, as we can see from the figures in Table 7. However, the result is still too poor to precisely find the PMLG case. Here we are giving an illustration of the inference result in experiment 11.

Figure 18: The illustration of TS09. a)inference PMLG result from experiment No.8; b)the reference data of tile.

From the image illustration, we can say that almost all PMLG cases might have been detected in varying degrees. However, the problem is that there are too many false positive cases in the results, also too many noises which take up only one pixel and isolated from others.

The poor result in both FCN-DKs and FCN-SegNet might be caused by the error in reference data. They are not 100% correct ground truth data. Still, the input imagery also contains the error of wrongly classified land cover pixels, which obviously decreases the model accuracy. Moreover, the huge imbalanced sample size in the number of PMLG pixels and Non-PMLG pixels also limits the learning ability of model. In the learning processing, model learns the case of Non-PMLG is far much more the case of PMLG. Thus, limited samples for learning PMLG pixels cause the machine to predict more pixels as Non-PMLG. It may also be the explanation of increasing F-score in experiment No.9 and experiment No.11.

From this experimental analysis, we can't conclude that deep learning technique is capable of detecting the potential micro land grabbing cases precisely. The first and foremost key to further confirming deep learning model's potential in solving this realistic land administrative problem is the quality and quantity of input dataset, also a good ratio between the sample size. However, we cannot summarize that deep learning model is unhelpful in detecting PMLG cases as the result of LULC classification is still impressive and has great value in other post-processing procedures.

4.2.3. Alternative method

Although the performance of using LULC result to do the PMLG cases detection is unsatisfactory as we showed in the start of section 4.3, the result of land cover classification is still impressive and its inference testing tiles are useful in finding potential micro land grabbing cases without using deep learning techniques but directly applying raster data analysis with the help of ArcGIS. Therefore, an alternative method for PMLG cases detection. Figure 26 helps to understand the logic of using raster arithmetic to find potential micro land grabbing cases.

As we inspect the data of registered land rights, parcels are usually composed of buildings and their attached gardens. By combining the classes "Buildings" (5) and "Garden" (1) in LULC as the privately-used land in the real situation and combining the left three classes as public land in reality, we obtained the data reflects the physical truth of land use situation. However, according to the experience summarized by the Kadaster project, that is micro land grabbing cases rarely happened in the form of building expansion. Therefore, we excluded the situation that LULC classification model inference the pixels as private used land while it belongs to the public land in the registered land right data.

Therefore, at the end of Figure 19, only the pixels in unique value "1" are the detected potential micro land grabbing pixels. They represent the situation that LULC classification model inference the pixels as the private used garden, both front and back, while it is the municipal land in the registered land right data. The illustration of the final result as Figure 20.

Inference pixel value	Label	Description		
1	Gardens	Private using		
2	Roads	Public	Pixel value	Label
3	Public Green	Public	of land right	
4	Water	Public	1	Public land
5	Buildings	Private using	2	Private lan

Table a: inferenced pixel value

Table b: reference of land right

By multiplying the pixel value of each pixel using "Raster Arithmetic", we have a new dataset:

New pixel value	Label	Description
1	PMLG	Where model inferenced as private used land, while it actually belongs to municipality/public land.
2, 3, 4, 5, 6, 8, 10	Non-PMLG	Where model inferenced as public land whether it belongs to public or private.

Figure 19: The arithmetic logic of using raster analysis to find potential micro land grabbing cases. (Table a: inferenced pixel value; Table b: reference of land right)

Result

Figure 20: a1) & a2)The illustration of raster arithmetic result; b1) & b2)The manually digitized PMLG data from Kadaster; c1) & c2) Overlaying analysis result of a) & b).

Following the procedures that can achieve the mathematical logic in Figure 26, we obtained a potential micro land grabbing map of this research. The processing time for each tile is around 15 mins. It can be seen from the images in Figure 20 a) and b) images, lots of detected PMLG cases using the raster arithmetic method are similar to the manually digitized data by Kadaster. However, it also shows some cases not in the Kadaster data. Since the Kadaster data is not one hundred percent correct, we cannot be sure if those missed cases are not PMLG cases. Thus, the processed data using raster analysis also needs in-site surveying.

4.2.4. Results assessment and comparison

To compare the result of raster arithmetic method with Kadaster manually digitized result, we are using the precision, recall and IoU. In precision-recall assessment, we actually take Kadaster result as the reference data. Therefore, true positive are overlaid PMLG pixels. Taking back to Figure 26, pixels in light blue are true positive pixels, this means land in light blue colour is identified as PMLG case not only by raster arithmetic method but also by the Kadaster method. The false positive are those pixels in pink, they are inference as Non-PMLG which opposite to the label in the Kadaster result. The false negative are those pixels inference as PMLG while the label in the Kadaster result is Non-PMLG, in colour orange of Figure 26. And pixels in dark blue in Figure 26 are the overlaid Non-PMLG pixels, also the true negative, it represents those land are regarded as the place has no potential micro land grabbing in both two datasets. Therefore, for the class "PMLG", precision here gives the ratio of overlaid PMLG pixels number to the

total pixel number of inference PMLG using deep learning model and raster arithmetic method. And recall gives the ratio of overlaid PMLG pixels number to the total pixel number of PMLG in Kadaster result. From the two confusion metrics of two experiments in Figure 27, it pixel number of TP, FP, FN and TN are shown. Followed the equation given before, we gain all the figures in Figure 28.

It is apparent from table 28 that the precision scores of PMLG class in both two experiments are much less than its corresponding recall score. In the first experiment, we can see raster arithmetic method predicts there are 1,095,747 PMLG pixels in images, which is 175% of Kadaster result. In the meantime, raster arithmetic method missing 369,541 PMLG pixels comparing to the Kadaster data. The average precision and recall of the "PMLG" pixels are 0.20 and 0.49, respectively. The relatively high recall value indicates that the proposed method detected almost half of the PMLG cases in the result of Kadaster method. For these two experiments, the overall IoU values are both beyond 0.5. It means the PMLG detection result obtained by using the geospatial analysis method in ArcGIS is similar to that obtained from Kadaster by using visual inspection in a large extent. The similarity(IoU) of these two data in class "Non-PMLG" is 0.97 and 0.98, respectively. However, the fact is that using the ideal LULC classification result of deep learning model to detect PMLG cases in ArcGIS raster analysis, we gain the IoU of PMLG cases is not that satisfactory comparing to the Non-PMLG cases. The IoU value of "PMLG" in both two trails is 0.14 and 0.17, respectively. This obvious numerical difference results from an imbalanced data sample.

Confusion Matrix LULC_ex3_RA		Raster A	Total Pixel number	
		PMLG	Non-PMLG	
Kadaster Result	PMLG	254921	369541	624462
	Non-PMLG	840826	57517112	58357938
Total Pixel number		1095747	57886653	58982400

Confusion Matrix LULC_ex5_RA		Raster A	Total Pixel number	
		PMLG	Non-PMLG	
Kadaster Result	PMLG	211692	190423	402115
	Non-PMLG	1154658	48443227	49597885
Total Pixel number		1366350	48633650	5000000

Table 8: The confusion metrics of two experiments.

Experiment	Precision of PMLG	Recall of PMLG	IoU of PMLG	IoU of Non-PMLG	Overall IoU
LULC_ex3_RA	0.16	0.56	0.14	0.97	0.56
LULC_ex5_RA	0.23	0.42	0.17	0.98	0.58

Table 9: The IoU result of PMLG class and Non-PMLG class.

In order to provide a detailed looking of the detection result by using raster analysis, we are here to give several zoomed cases. In the figure below, we are taking the Kadaster data as the reference data in order to name the different situations. Therefore, the positive class is PMLG pixels in the Kadaster data while negative class is Non-PMLG pixels in the Kadaster data. In Figure 28, the back garden of 5 parcels all have a potential micro land grabbing situation. Inhabitants would like to extend their garden to the public green area. This situation is well-detected by proposed methodology.

Figure 21: The true positive case of PMLG. (PMLG pixels in both raster arithmetic method result and Kadaster result)

In Figure 29, a false positive case displayed. For this greeny plot close to a building, we recognize it as PMLG cases but the Kadaster data take it as legally used land. Figure 30 shows a false negative case, where we detected no PMLG situation happened in the area of pink color, but it is a PMLG case in the Kadaster manually digitized data.

Figure 22: The false positive case of PMLG. (PMLG pixels in raster arithmetic method result but Non-PMLG in Kadaster result)

False negative PMLG PMLG NonPMLG Figure 23: The false negative case of PMLG. (Non-PMLG pixels in raster arithmetic method result but PMLG in Kadaster result)

In this post-processing method, we obtain the map that distinguishes all the pixels into PMLG and Non-PMLG pixels (Figure 20, a1) & a2) images). By applying the Precision-Recall-F-score and IoU metric, we

perform the comparison of our obtained map with Kadaster manually received map. The intersection part (the true positive cases) of these two results further ensures the probability of potential micro land grabbing happened in those land. At the same time, the union (also contains the false positive and false negative cases) excluding the intersection part are those land with the uncertainty of potential micro land grabbing phenomenon.

In general, the overall result proves that deep learning model together with raster analyzing is useful in detecting the micro land grabbing cases in the Netherlands. Comparing the method of using two deep learning models as in section 4.2.2, which can be regarded as a fully learning-based method, this automatic method provides the more reliable final result.

5. DISCUSSION

5.1. Result discussion

In this research, we investigates the method used in the Netherlands to find potential micro land grabbing cases at the current moment. The Kadaster is currently using a traditional visual inspection approach. Although this method is time-consuming and laborious, it guarantees data accuracy greater than 90%. Based on the result of interview and related literature review, several temporal and spatial characteristic of micro land grabbing situation in the Netherlands are summarized. For example, the neighbourhoods with older buildings (i.e., from 1940 or before) with larger front and backyards have higher rates of land grabbing; and it rarely appears in the form of house extension. However, due to the sensitivity of the data, and the later checking work is undertaken by the local municipalities or other customers, Kadaster has not a system in place to provide 100% correct PMLG reference data at this moment. Completing the case review of illegal land use in the Netherlands has always been one of Kadaster's priorities. In recent years, with a heatwave of artificial intelligence and deep learning, Kadaster also seeks the opportunity of using high-end technologies to improve the efficiency and effectiveness of micro land gabbing recognition.

In order to realize the monitoring of PMLG cases, this thesis put forward an automatic method. We test the effect of different hyperparameters of FCN-SegNet to LULC classification accuracy as a starting point for PMLG detection. We used different base learning rates to find the optimal learning rate for this research, it is 0.01. Training the different models in 100 or 50 epochs, we find that set the number of epochs to 50 is sufficient for the classification model to learn in the content of this research. Among the eight LULC classification experiments, the No.5 experiments using only the data of Zoetermeer gains the highest average F-score. Among five LULC classes, class "Buildings" stands out in the testing result, its F-score all close to 0.90 in each experimental analysis. However, class "Garden", which is the critical class for detecting the micro land grabbing cases, gains a relatively low F-score, from 0.67 to 0.8. The class "Garden" is more complex compared to others. Mixed visual cues are visible in gardens, including not only outdoor tables, sheds and vehicles, but also man paved roads and green areas that share the same features as the class "Roads" and "PublicGreen".

All in all, LULC classification experiments prove deep learning model can produce land cover classification data with considerably high accuracy. Taking advantage of the available training data, supervised FCN-SegNet has the capability of learning to classify the different land cover, and labelling each pixel in the testing tile. In addition, even if we combined the geographic data that covers difference municipalities and acquired in different data, like the VHR imagery covers Zwolle and Zoetermeer while acquired in 2016 and 2019 respectively, deep learning models are still able to perform LULC classification without accuracy decreasing significantly, and the overall accuracy is above 82% with the average F-score reaching 0.841.

After obtaining the satisfactory LULC classification result, we put them separately into the second deep learning model in an endeavor to find the PMLG cases. In this procedure, two deep learning models have been applied. However, the obtained results are not satisfactory. Comparing to the FCN-DKs, FCN-SegNet has slightly better performance in PMLG detection. We attribute the poor performance to three reasons. Firstly, the error in the reference data. Reference data are manually digitized, and they are not 100% correct. Secondly, the input imagery contains the error of wrongly classified land cover pixels. At last, the substantial imbalanced sample size in the number of PMLG pixels and Non-PMLG pixels.

Since the fully automatic method that using two deep learning models failed to provide the precise interpretation of the detected PMLG cases. An automatic method adopted, that is using the LULC deep

learning classification model together with the raster arithmetic analysis. In this process, the result of LULC classification and registered land right data are used to generates the PMLG maps, whose pixels are divided into PMLG pixels and Non-PMLG pixels. The manually digitized Kadaster data in this process becomes the comparable data. Based on average 0.2 precision value of "PMLG" class, we found the proposed method regards many Non-PMLG pixels in the Kadaster result as PMLG pixels. However, the PMLG cases detected by the proposed methods are almost half of the result obtained by Kadaster method as the average recall value is 0.49. Moreover, by applying the IoU metric, we find the similarity between this automated method's result and Kadaster data are stabilized around 97%. In the first experiment using the LULC experiment No.3, the IoU score of Non-PMLG is 0.97, while the score of PMLG is 0.14. In the second experiment using LULC experiment No.5, the IoU score of Non-PMLG is 0.58. Summarizing the above, we can determine that the proposed method can automatically detect PMLG cases with certain accuracy.

5.2. Research limitation

5.2.1. Data criticism

As we have emphasized several times in the text, the PMLG data was manually digitized by Kadaster's professionals is not 100% correct. This fact directly leads to unsatisfactory training results when we used the DL model again in the second part. From the perspective of deep learning models, it relies on the kind of data with errors for learning. This data contains both true information and false information, even confusing to human beings, thus, increasing the uncertainty of learning result. Still, this also reflects the difficulties of land data management.

5.2.2. Reflection on deep learning

Deep learning in recent years has a large number of achievements, it has wide applications. Undeniably, the deep learning model is based on a particular algorithm and program set, and its recognition mechanism is completely different from human sensory recognition. Therefore, in graphic recognition, like text, fingerprints and other clear graphics, deep learning model can quickly identify the cases of interest, but for a problem like potential micro land grabbing, which involves logical thinking about legislation, deep learning model shows limited capability.

It is true that deep learning helping in reflecting the physical reality from the imagery, like the land cover classification and land use change detection, however, it is hard to tell the truth that if this detected result is really of interest. Based on the result of section 4.2.3, we can say deep leaning model recognize potential micro land grabbing cases in a certain extent, which is not equivalent to the machine understands what happened in real-life. In fact, the cases we have detected are the land use changes, it includes not only the potential micro land grabbing cases, but also other lands that are under a legal change. Of course, it may also attribute to the lag of the data, failed to update the official cadastral data in time. But the fact is that we cannot describe the process of grabbing land directly, which includes how the illegal land activity happened step by step and who did this, which is also a common problem in the visual inspection of using single-year remote sensing images.

From another perspective, the industry should not only pay attention to the efficiency of the algorithm, but also pay attention to whether its design itself conforms to ethical standards, and whether it can be accepted and trusted by the public. Therefore, another aspect worthy of consideration is the issue of public trust, that is, whether people trust the results of machine learning, or the degree to which people can accept the judgment of machine learning on the benefits of designing humans. Labeling a parcel has the potential micro land grabbing situation, it not only directly affects the economic interests of landowners and leads to direct economic losses, but also affects the problems of personal credit and governmental trust. This is not a trivial

matter. It takes courage to put a deep learning model into the market. Who should be held accountable when the model harms personal interests? How should we understand this hazard and how to remedy it? Those are the questions we need to discuss in advance. In the research of this thesis, it takes only a dozen seconds to inference an image and divides the pixels on it into PMLG and Non-PMLG, but this process is irreversible. Without post-processing or filed checking, the result cannot deliver to a customer directly.

An unavoidable fact is that only after humans have not fully understood or solved the micro land grabbing situation with human wisdom, the existing technology and existing data are sufficient to enable deep learning models to detect potential micro land grabbing cases independently. We cannot completely rely on artificial intelligence while excluding the real human intelligence.

5.3. Ethical consideration

As we mentioned above, when a land use boundary is not coinciding with a cadastral boundary, we cannot speak automatically of micro land grabbing. More research (including legal) is needed to determine if it is land grabbing or not. Considering this, the term "potential" should be emphasized.

Moreover, it is true that the automated method proposed in this research is capable of extracting the valuable spatial information from the imagery and using the output results as a guidance to confirm the potential micro land grabbing cases in the filed checking, but the whole methodology works only under a proper framework. This means, imagery used removes all the individual related information, like the portrait and license plate number. It is not allowed to relate any geographic location to a specific individual's name or address. And it should be claimed that the produced results mainly follows a logical method of scientific research, which may contradict legal facts. The potential risk to use proposed method and its results exist.

Besides, the consent of Kadaster should be sought before any future study uses related data and result of Kadaster method that are described in this research.

6. CONCLUSION AND RECOMMENDATION

6.1. Conclusion

The main purpose of this study is to propose an effective and novel machine-learning-based method that could facilitate the process of detecting potential micro land grabbing in the Netherlands proactively and thus in support of Dutch land administration. This generic objective is subdivided into three specific objectives. By answering the following nine research questions, the final conclusion is drawn.

Objective 1: To identify the current methods for micro land grabbing detection in the Netherlands.

- 1. What methods are being used for detecting micro land grabbing cases in the Netherlands currently?
- 2. What issues are related with detecting micro land grabbing in the Netherlands?

Currently, the task of micro land grabbing detection divides into data preparation and field checking. To prepare the reference map of potential micro land grabbing, the traditional visual inspection method applied in the Kadaster. Remote sensing imagery together with the professionals' rich experience are main basis. Among this process, the issues can be concluded into: unclear methodology, repetitive working, huge time and cost investment, intrinsic sensitivity, etc.

Objective 2: To develop a deep learning algorithm for detecting potential micro land grabbing cases and thus monitoring the development of micro land grabbing in the Netherlands.

- 1. Which deep learning network architecture is appropriate for detecting potential micro land grabbing cases?
- 2. What geospatial data are needed to detect potential cases of micro land grabbing?
- 3. How to design the training and testing data?

4. How to distinguish the potential micro land grabbing cases by using the deep convolutional network? Semantic segmentation is the main task of this study. SegNet achieved impressive LULC classification result after we optimized the hyper-parameters through a systematic model-tuning. In the second process of detecting the PMLG cases, both SegNet and FCN-DKs adopted. For the required geospatial data, aerial imagery that covered two selected study areas collected. Supportive geographic data includes the reference data of land use land cover, registered land right map. Comparative data is the potential micro land grabbing result that manually digitized by Kadaster. In total, forty-four tiles are selected from two sites and then split into training data and testing data randomly. The tile size in Zwolle is 2500×2500, while in Zoetermeer it is 2560×2560. The spatial resolution for all the input images and related geospatial data is 0.1 m. Adopted deep convolutional network learns the feature of each land cover class in all training tiles, and then generates the inference land cover classification map. This output together with the registered land right information are used to distinguish the potential micro land grabbing cases.

Objective 3: To evaluate the results of the proposed method and compare it with the traditional method applied in the Kadaster.

- 1. What is the reliability of the proposed method in detecting potential micro land grabbing?
- 2. What are the comparing results of the proposed method and Kadaster current method?

Using the proposed SegNet, LULC classification experiment carried in the Zwolle achieved an average F-score of 0.827 in model testing. And in the Zoetermeer, this F-score is 0.864. Experiment using the data

that combining the Zwolle and Zoetermeer images all gain a high F-score, 0.841. However, in the final step to detect PMLG, it is hard to check the model result accuracy as there is no 100% correct reference data provided. The reliability of proposed method shows in the logic workflow of this research. Proposed method can reflect the physical truth of land cover in aerial imagery. And this automated method for PMLG detection can provide certain valuable spatial information, and can be used as general guidance before the manual digitization processing of the professionals in the Kadaster.

The comparing result shows that the proposed method finds almost half of the PMLG cases that also shown in the Kadaster result. Comparing to the result of Kadaster method, proposed method inferences that there are more PMLG cases in the same tiles. However, it also missed some PMLG cases. The extra and missing PMLG cases of proposed method referred as false positive and false negative, respectively. In the long-term, proposed method has an absolute advantage in processing time. Once the LULC model is well-trained, it takes only few seconds to have a well-classified map result. The time for post-processing, raster arithmetic calculation, is only 10 to 15 minutes for each tile.

6.2. Recommendation

To achieve a better LULC classification result, there are many strategies that can be applied. In the content of this research, the aerial images we loaded have only three bands (RGB). Using the multispectral image, it is possible to further improve the LULC classification results, especially in the classification of buildings and vehicles. Correspondingly, the final PMLG detection result improved. At the same time, including DSM (digital surface model) information for each pixel in the research tiles might also raise the results. Essentially, people usually stand up the fence around the land they are using in order to exclude the entry of other people. This obvious height difference helps the model in distinguishing the private garden and its around public land.

Another suggestion is that Kadaster needs to clarify the definition of micro land grabbing cases. This includes not only textual explanations, but also a spatial illustration. For example, Kadaster needs to indicate the area range of the micro land grabbing case, that is, the spatial distribution characteristics, like whether it only occurs on the surface, or it will also occur in underground space and in air.

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