Using GeoAI in Property Valuation

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SUMMARY

Property taxes fund government services. In developing economies, such recurrent sources of funds are hard to generate or not fully optimized, often caused by lack of up-to-date data and resources needed for property valuation. This paper argues that the use of GeoAI could improve property valuation in developing economies by providing up-to-date inputs to valuation process in a more efficient and cost-effective manner.

GeoAI—the combined application of AI, GIS, remote sensing, and big data technologies in solving problems—has become increasingly popular in the field of property valuation, and land administration in general. Such trend is characterized by increasing use of AI in remote sensing, the prevalence of high spatial resolution images from satellites and unmanned aerial vehicles (UAV), the growing sophistication of GIS tools that integrates deep learning algorithms, and adoption of big data platforms such as cloud computing. As demonstrated by the case study in Lusaka City (Zambia), GeoAI has the potential in speeding up the simplified valuation process in a more efficient and cost-effective manner by providing building area estimates at a fraction of the time and cost required to conduct house-to-house surveys.

The authors, therefore, support the vision towards the development of standards on the use of AI in property valuation. Such standards will not only provide valuers in developed economies additional tools for valuation, but also guide the use of GeoAI to complement existing valuation process in developing economies. In this context, professional organizations could play a key role to drive the adoption of AI for property valuation through standards, education, training, and so on.

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1. INTRODUCTION

High cost of accurate valuation and political difficulty of enforcement were identified as serious disadvantages of property tax (Bahl et al., 2008; Reydon & Louwsma, 2021). Often, property tax does not reach its full potential as a revenue-raising instrument because of poor assessment practices. For developing economies that depend on property tax to raise revenue to finance government services and/or influence social policy and economic decisions (e.g., better use of land), fit-for-purpose valuation is important. Failure to establish a credible tax valuation erodes tax payer confidence, dampens compliance rates, and limits revenue performance (Bahl et al., 2008).

As shown in Figure 1, valuation process differs between developing and developed economies. The differences are mainly due to availability of data and resources to perform valuation. In developed economies, AI applications tend to concentrate in Stage 2 (valuation modelling) as AI methods are often proposed as an alternative or replacement for current valuation methods. Moreover, AI may have been applied to some degree in Stage 1 (data preparation) and Stage 3 (test if valuations are accurate, consistent, and unbiased). Given the data and resources available, computer-assisted mass appraisals (CAMA) or automated valuation models (AVM) are common in developed economies.

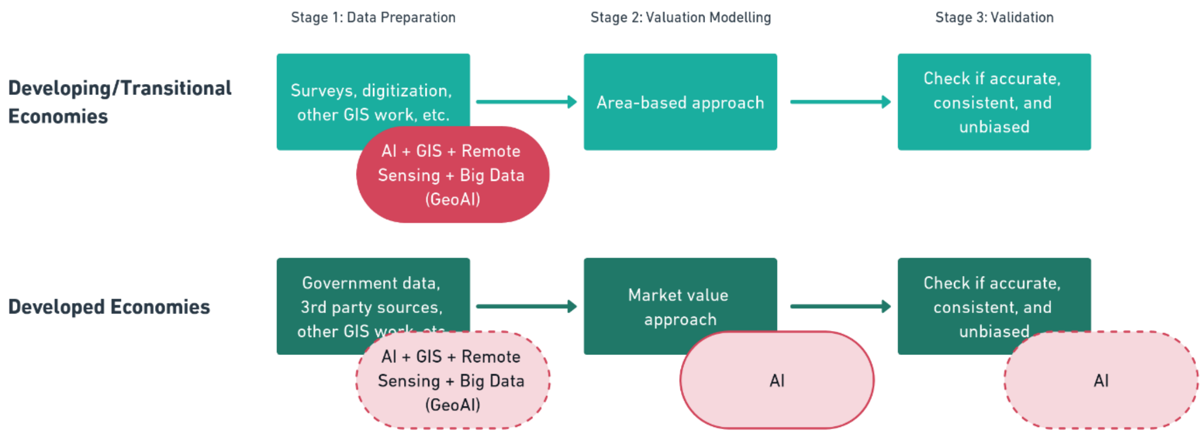

Figure 1. Highly simplified view of property valuation process in developing and developed economies that highlights AI application in various stages.

The focus of this paper is on the practical application of GeoAI to support tax valuation in developing economies (Figure 1). GeoAI refers to the combined application of AI, remote sensing, GIS, and big data technologies in solving problems (Janowicz et al., 2020; Li, 2020). The popular valuation method in developing economies is the area-based approach. The approach involves two steps: 1) every property is assigned a value zone based on location, services available, and quality of structure, and 2) the taxable area of the property is multiplied by a determined value per square foot to arrive at the property tax base (Bahl et al., 2008; McCluskey et al., 2013). With this approach, GeoAI can be used to automate some of the data preparation steps (Stage 1) prior to valuation (Stage 2).

This study is important because there is limited work in the use of GeoAI that supports property valuation when there is limited data and resources, particularly in developing economies. In contrast, there has been a lot of focus on the use of AI methods in valuation either as an alternative or replacement to existing methods in developed economies. This paper argues that the use of GeoAI could improve property valuation in developing economies by providing up-to-date inputs to valuation process in a more efficient and cost-effective manner.

2. LITERATURE REVIEW

Property tax, herein defined, refers to recurrent tax levied on real estate such as land, buildings, or both (Franzsen & McCluskey, 2017). To levy property tax, all properties must be subjected first to valuation. In this section, we discuss current trends in property valuation, particularly the increasing popularity of automation and mass appraisal. Also, we review the components of GeoAI in the context of property valuation. The authors believe that GeoAI has tremendous potential, particularly in developing economies where there are limited resources for tax administration.

2.1 Property Valuation

Property value is determined either: (1) based on the value of the property (an ad valorem tax base), or (2) a non-value assessment, which is the product of factors that influence property value and areas of taxable property (Plimmer & McCluskey, 2016). The first type of valuation is known as value-based, which is common in developed economies due to available transaction data from mature real estate markets and sufficient resources for tax administration (e.g., professional valuers and advanced valuation tools). In contrast, the second type generally refers to area-based valuation, which is common in developing economies where industry standards practiced in developed economies are not applicable.

As identified by Plimmer & McCluskey (2016), the resources needed for an effective and efficient property tax system, at the minimum, include:

1. Data on real estate tax base (e.g., registered landowners)

2. Capability to perform tax assessment (human & technology)
3. Ability to influence social acceptance (e.g., educating taxpayers)
4. Administration which involves billing, collection, and enforcement

The shift from single property appraisal to mass appraisal was a practical one, if not evolving from the desire for uniformity and consistency (McCluskey & Adair, 2018). Given the vast number of properties to be evaluated in every revaluation period, it is costly and therefore impractical to appraise individually. Over time, the increasing volume of transaction data along with advances in computing technology and valuation algorithms has cemented the use of CAMA systems, which often include various implementation of AVMs. Unfortunately, it is rare to find mass appraisal being implemented in developing economies due to lack of data and capabilities for tax assessment (McCluskey & Franzsen, 2018). Also, developing economies are faced with lack of valuers to establish and maintain an updated valuation roll, which is a critical component of an effective tax administration.

Despite the rapid advances in CAMA methods (Wang & Li, 2019), even among developed economies, the search for the best model continues—exacerbated by volatile real estate markets (Voss & Ache, 2021) and expanding sphere of valuation purposes (Shapiro et al., 2019). As valuers like to mention, no one model fits all. To remain relevant and competitive, valuers are always looking for approaches that yield better predictive accuracy and cost-effective than the last method used. These situations led to the rise of AI in property valuation, which some claimed to be more accurate and cost-effective than traditional approaches (Bidanset, 2019; Dorigo, 2020; Kok et al., 2017; Wang & Li, 2019; Zurada et al., 2011).

2.2 AI Applications in Valuation

AI involves the use of computers and algorithms to automate tasks or make predictions better than traditional approaches. In this paper, we refer to AI to include categories with practical applications to property valuation, ranging from machine learning (ML) (Pinter et al., 2020; Su et al., 2021; Yilmazer & Kocaman, 2020; Yoo et al., 2012), deep learning (Crommelinck et al., 2019; Hossain & Chen, 2019; Persello et al., 2022; Yazdani, 2021), natural language processing (de Vries, 2021), among others. In mass appraisal, traditional approaches refer to multiple regression analysis (MRA) and its variants (McCluskey & Borst, 1997; McCluskey & Adair, 2018; Zurada et al., 2011).

Large majority of AI applications in property valuation have mainly focused as an alternative or replacement to existing valuation methods (Bidanset, 2019; Goldfarb et al., 2021; James, 2018; Jensen, 1990; McCluskey et al., 2012; McCluskey & Borst, 1997; McCluskey & Adair, 2018; Rayburn & Tosh, 1995; Wang & Li, 2019; Zurada et al., 2011). This has been the trend in developed economies given the availability of data and expertise. AI applications include the use of artificial neural networks, expert systems, tree-based and hierarchical models (random forests, gradient boosting methods), cluster analysis, rough set and fuzzy set theories, reasoning-based models, and other models such as genetic algorithms and support vector machines (Gloudemans & Sanderson, 2021; Wang & Li, 2019).

In general, AI applications tend to concentrate on academic research, primarily focusing on predictive accuracy of AI methods relative to traditional approaches (McCluskey et al., 2013; Shi et al., 2022; Yacim & Boshoff, 2018; Yilmazer & Kocaman, 2021). Recently, however, an attempt by Property Valuation Services Corporation (PVSC) in Nova Scotia, Canada, to investigate the use of ML led to a proof that AI can be deployed in actual valuations (Gloudemans & Sanderson, 2021; Goldfarb et al., 2021). According to Goldfarb et al. (2021), PVSC became the first Canadian jurisdiction to incorporate ML into mass appraisal.

Valuers think that AI helps reduce cost of property valuation, works more efficiently than traditional valuation methods, reduces subjectivity, frees valuers from onerous work of valuation, and provides more accurate estimates than traditional approaches (Abidoye et al., 2021). Despite these advantages, barriers remain strong that hinder AI adoption in property valuation. The top barrier is that valuers perceive AI methods may not provide accurate valuation estimates (Abidoye et al., 2021). But studies have shown that AI predictive accuracy was at par with traditional methods, if not outperforms in most cases (Goldfarb et al., 2021; McCluskey et al., 2013; Taffese, 2006; Zurada et al., 2011).

Such disconnect may be attributed to the “black box” nature of AI (McCluskey et al., 2012) and tendency by valuers to stick with status quo out of fear of getting replaced or fear of losing the importance of their current roles in the valuation process (Dorigo, personal communication, April 2022; Goldfarb et al., 2021). “Black box” nature of AI refers to the lack of transparency or explainability, which remains a sticking point for AI adoption (Dorigo, 2020; McCluskey et al., 2012; McCluskey & Borst, 1997). Other observers remain pessimistic about AI’s adoption, citing that AI is still far from replacing human experts (Shapiro et al., 2019; Pipitone, 2022).

In our conceptual framework (Figure 1), the challenges for AI adoption are different for developed and developing economies. In developing economies, AI is not commonly applied in estimating property values (Stage 2), although this might be possible. Given lack of data and expertise, simplified area-based assessments remain the typical valuation approach. Such approach may not be replaced soon as simplified area-based assessments are found to be as effective as those complex systems found in developed economies (Davis et al., 2012), aside from being the only practical approach available (McCluskey & Franzsen, 2018). However, this approach relies on printouts, out-of-date cadastral maps, and manual measurements of property and improvements that are considered inefficient and costly (Franzsen & McCluskey, 2017; Koeva et al., 2021). In the next sections, we discuss trends in GIS, remote sensing, and big data technologies that can be applied together with AI to complement existing valuation systems in developing countries.

2.3 GIS and Remote Sensing

Recent trends point to the use of GIS- and AI-based models, and mixed methods in mass appraisal (Wang & Li, 2019). Wang & Li (2019) dubbed it as ”mass appraisal 2.0”, which is characterized by the proliferation of valuation methods that utilize both spatial and non-spatial data, and GIS/AI algorithms.

GIS has a long history with property valuation as the platform for the capture, management, and visualization of property data (Clemens, 1992). With the advancement in geospatial analysis techniques, the traditional regression methods take on various forms to accommodate location effects often implemented in GIS environment (Bidanset et al., 2017; McCluskey et al., 2013). Some like Yang et al. (2015) used a web GIS to display land price information accessible through the Internet.

Along with GIS, the availability of satellite and unmanned aerial vehicle (UAV) or drone images usher in the use of remote sensing techniques in generating data that feeds into different valuation methods (Bennett et al., 2021; Crommelinck et al., 2019; Dimopoulos et al., 2015; Koeva et al., 2021; Nyandwi et al., 2019; Wang et al., 2020; Zhang, 2019). In tandem with GIS, high spatial resolution images are processed to extract features such as parcel boundaries, building footprints, road centerlines, and so on (Hossain & Chen, 2019; Nyandwi et al., 2019; Wang et al., 2020; Xia et al., 2019; Zhang et al., 2018). Such derived data are further processed in GIS to generate additional features for valuation methods (García et al., 2008; Hermans et al., 2021; Mimis et al., 2013). As will be demonstrated later, drone imagery was used to extract building footprints for an area-based valuation.

2.4 Big Data Trends

AI continues to advance, thanks to big data technologies that allowed processing and storage of massive data that fuels most of AI models (Dorigo, 2020; Wiersma et al., 2017). Aside from storage, cloud computing speeds up training of deep learning (DL) models used in extracting objects from imagery (Asaftei et al., 2018; Koeva et al., 2021). Moreover, big data computing as embraced by GIS applications led to the integration of GIS and DL algorithms (Mohan & M.v.s.s, 2022). Such integration allows data preparation, training, inference, and postprocessing for extracting objects from high spatial resolution imagery in the same GIS platform. Also, big data technologies enables continued development of AVMs as applied to real estate (Asaftei et al., 2018; Dorigo, 2020; Kok et al., 2017).

2.5 Summary

Current trends on CAMAs or AVMs tend to be influenced by development in technology, which brings together AI, GIS, remote sensing, and big data (collectively known as GeoAI) to property valuation. Given the rapid changes in real estate markets, the deluge of data from many sources, increasing popularity of AI tools and cloud computing, and desire of government and private sectors to be up to date with property valuations—all these factors combined—drives research and application of AI in valuation. AI finds a lot of applications across stages of the valuation process (Figure 1), developing economies are no exception. Hence, the case study in the next section demonstrates the value of GeoAI to enhance simplified valuation approaches in developing economies by more efficient and cost-effective generation of inputs to valuation process.

3. CASE STUDY: LUSAKA CITY, ZAMBIA

Zambia has grappled with implementing the land titling from 2018 when it started the piloting of the National Land Titling Programme through the seventh National Development Plan (2017-2021). The implementation started with a small pilot project conducted in Lusaka City in areas called Madido and Kamwala.

In 2018, the Ministry of Lands and Natural Resources (MLNR) signed an MoU with Medici Land Governance Inc. (MLG). MLG, a public-benefit company that provides user-friendly, low-cost land titling and administration systems, has agreed to conduct another larger pilot to collect landownership information for 50k land parcels in Lusaka City. MLG used modern technology, such as UAV imagery and AI for identification of property boundaries, tablets and apps to collect ownership information from landowner, and automated production of survey diagrams and general plans of areas.

MLG led the systematic land titling (SLT) pilot and accelerated the titling of 50k+ parcels by using a mobile application that included pre-vectorized high-resolution images, efficient house-to-house data and signature gathering from homeowners, community verification, and ML to validate data accuracy. MLG collected this data to support:

- Simplified and expanded land titling
- Regularizing unplanned settlements and preventing displacements
- Reducing inequalities of access to land ownership due to income differences
- Increasing the revenue base and investment in the country

Following the success of this pilot, the Lusaka City Council (LCC) partnered with MLG to lead its property titling program and develop and deploy a Land Governance Platform (May 2019), which includes the administration of subsequent registrations, valuation, and taxation.

3.1 Property Valuation at Lusaka City

In enumerating parcels as part of the titling program, UAV orthophotos were generated for various areas in Zambia, which includes that of Lusaka City—the nation's capital. As suggested by Koeva et al. (2021), UAVs have the highest potential for collecting data to support property valuation. In the case of Lusaka City, 40km x 40km image tiles with 5cm spatial resolution were mosaicked (Figure 2) to be used as input to GeoAI solution to extract building footprints, one of the inputs to LCC's simplified property valuation.

The simplified property valuation uses the Tone of the List, which assigns valuation factors to different areas or zones (Figure 2). Such valuation factors include land valuation per hectare of parcel area and building (i.e., land improvements) valuation per square meters of building area. The tax base or rateable value is simply the sum of valuations for parcels and buildings. MLG’s SLT solution along with existing cadastral records were used as data source for parcel areas to calculate land values. However, measuring land improvements as represented by building areas remain a tedious and expensive process. In developing economies, current approach of capturing building areas involves house-to-house inspections using tape measurements, handheld GPS, and digital cameras (Koeva et al., 2021).

With large majority of rateable value consisting of valuation for buildings or land improvements (60-80%), this major bottleneck in property valuation for LCC needs to be addressed. MLG agreed to work on a proof of concept to leverage GeoAI to automatically extract building footprints from UAV orthophotos.

Figure 2. Lusaka City with Tone of the List boundaries superimposed on UAV orthophotos

3.2 Building Footprint Extraction (BFE)

House-to-house inspections to gather information in the field, such as building areas, are expensive and time consuming. In this case study, the problem is to automate the extraction of building footprints from UAV orthophotos (drone imagery). Image segmentation methods are often used for building footprint extraction (BFE) that uses DL algorithms—a sub-category of ML algorithms typically used in computer vision tasks (Rastogi et al., 2020; Touzani & Granderson, 2021). At a high level, BFE process starts with drone image, which is fed into a trained ML model to generate a binary classification image (building, non-building) that is transformed into building polygons, a process known as vectorization.

Selecting and training the appropriate ML model is a non-trivial task. To quickly prototype, we decided to limit the choice of segmentation algorithms, focusing on what is currently available to MLG team. Also, we decided to compare segmentation approach using open source versus commercial applications. The motivation is to provide tax administration agencies or private organizations in developing economies with a choice of GeoAI implementation that is appropriate for their needs given expertise and budget constraints.

As shown in Figure 3, the three BFE models we implemented include:

- BFE1: semantic segmentation implemented using fast.ai, U-net architecture (open source)
- BFE2: similar to BFE2, but reduced training sample and increased training epochs twice that of BFE1 (open source)
- BFE3: instance segmentation implemented using ArcGIS API, Mask R-CNN architecture (commercial)

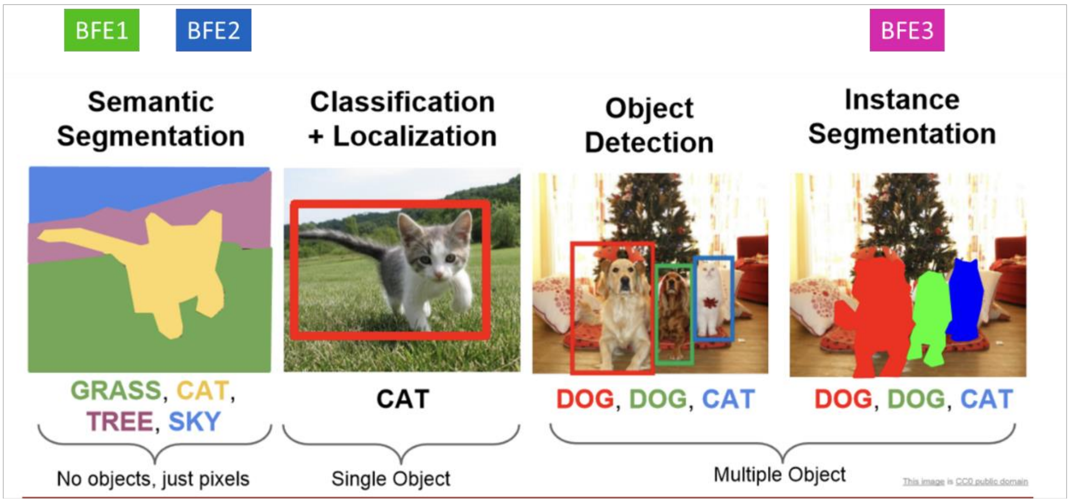

Figure 3. Different image segmentation and classification models (Li et al., 2017)

Semantic segmentation models (BFE1 and BFE2) were implemented using fast.ai framework and written in Python. All components have to be written from scratch, particularly the vectorization of classified image generated during the ML inference stage. In contrast, instance segmentation (BFE3) using a commercial software, ArcGIS Pro, has already a built-in vectorization component embedded as part of its model inference method. Therefore, there is less code in implementing BFE3 than the other models. BFE1 and BFE2 used a mixture of training samples from OSM, SpaceNet, and UAV orthophotos of Lusaka City, while BFE3 only used digitized buildings from UAV orthophotos and Tone of the List areas for stratified sampling. Residential buildings in Lusaka are dominantly single-storey buildings, which was the focus the case study.

3.3 Methodology for Evaluating Model Performance

In comparing the three BFE models in terms of how accurate they predict building areas, 100 test blocks were defined, with each block the size of 50m x 50m (Figure 4). Such dimensions were selected as it was manageable to digitize buildings inside the block. Also, the block size is small enough to minimize individual building areas to cancel out—giving the wrong impression that the model performs well when it is not. Buildings in each block were digitized so the total building areas for each block can be calculated. Total areas in each block were used as the benchmark to compare area estimates from different models. Test blocks were selected to represent key residential bands (zones) and semi-randomly located to avoid picking the same blocks used for ML training.

Figure 4. Methodology for evaluating performance of building footprint extraction models

To evaluate model performance based on valuation estimates, cadastral valuations for residential properties in 2019 from LCC was used as the benchmark. Since the drone imagery was taken in 2021, a subset of cadastral valuations was finally selected to ensure that only parcels with residential buildings were included. This is to avoid inclusion of parcels without buildings in 2019 but may have buildings in 2021. So, the rateable values or property valuations based on cadastral data are comparable with valuation estimates using inputs from different BFE models.

4. RESULTS AND DISCUSSION

For GeoAI applied to building footprint extraction, which BFE model is the best in terms of accuracy, time, and cost? Also, it will be important to evaluate which model results into valuation estimates similar to cadastral valuations that used manual house-to-house inspections.

4.1 Which BFE Model Is Better?

To evaluate, the following metrics were used (Table 1): (1) *accuracy*: how close are building area estimates from the model relative to test blocks? Root Mean Squared Error (RMSE) was used to penalize models with higher variance—the lower the RMSE, the more accurate the model; (2) *time*: time required to prepare data, train model, and predict building footprints from imagery, and postprocessing results to be ready as input to tax valuation; and (3) *cost*: license, cost of development and maintenance.

Table 1. Comparison of image segmentation models applied to building footprint extraction

Model	Accuracy (RMSE)	Time*	Cost
BFE1 (semantic segmentation, version 1)	69	90+ hours**	Free
BFE2 (semantic segmentation, version 2)	156	90 hours	Free
BFE3 (instance segmentation, version 1)	51	52 hours	US$8,400/year or US$25,000 perpetual (ArcGIS Pro license, includes Image Analyst extension)

*Processing time comparison excludes time spent on data preparation needed for model training. It only includes time spent on model training, prediction, and postprocessing. Estimate applies to 100 image tiles (40km x 40km, 5cm spatial resolution). See below for detailed breakdown on processing time by ML stage.

**ML was implemented by someone else, however this is like BFE2 so processing time could be higher especially when including data preparation.

Breakdown of processing time by ML stage:
<u>Data preparation:</u>
- BFE2: not sure how much was manually generated (used external sources)
- BFE3: ~6 hours (manual digitization, avg 3 buildings per minute)

<u>Model training (GPU RTX 3060 6GB):</u>
- BFE2: 5,076 chips (10k+ buildings), 202 minutes, converged after 9 epochs
- BFE3: 1,839 chips (1k buildings), 91 minutes, converged after 16 epochs

<u>Model prediction and postprocessing:</u>
- BFE2: avg 52 minutes per 40km x 40km image tiles
- BFE3: avg 30 minutes per 40km x 40km image tiles

From data preparation to postprocessing, BFE3 took 2.2 days to extract building footprints from imagery of a city covering an area of 160,000 km^2 with a population of 3 million (Table 1). BFE2 took at least twice as long, BFE1 maybe more. But compared to boots on the ground measuring building areas that take months or more to finish, the use of GeoAI is a tremendous improvement that translates to time and financial savings. Even if we add 4-6 weeks to account for training data preparation, QA/QC of building footprints, there remains massive savings. *In a similar study, Konstantinos & Pratomo (2021) estimated cost savings of 30,000 EUR/year for an area 160 times smaller than Lusaka City.*

Assuming we are indifferent in terms of cost but sensitive to accuracy and processing time, then BFE3 model is the best choice. Even if taking cost into account, BFE3, which is dependent on ArcGIS DL libraries, remains a better choice. Aside from being a full-fledged GIS tool, ArcGIS Pro offers ready-to-use ML models useful for other object detection purposes. For example, DL models for road extraction and building height estimation are available and could be easily fine-tuned to various use cases. For open-source applications, development time can easily rack up to the license costs of ArcGIS Pro. However, if done right, use of open source may save more in the longer term as continued dependence on commercial software may cost more.

In terms of MAE (mean absolute error; Table 2), BFE1 tends to vary from actual building areas by 44m^2 in Band I, less bad in Band E. Both BFE1 and BFE2 did worse in Band K, which is due to incomplete buildings, not included in the test samples, but detected by BFE1 and BFE2 models. BFE3 has the lowest errors in all test blocks except in Band A, likely due to commission errors (e.g., misclassified pools as buildings). However, BFE3 tends to be robust in detecting most of the building areas despite the presence of tree canopies.

Table 2. Comparison of BFE model performance across different test areas

Residential Band	# Test Blocks	MAE (m^2)		
		BFE1	BFE2	BFE3
I	25	44	55	28
E	25	20	79	25
K	25	66	86	26
A	25	37	27	42

An obvious solution to the issues mentioned above is to increase training samples for areas where the model performed poorly. Also, further data cleaning such as editing boundaries of building footprint to minimize building area errors. In some cases, removal of non-building objects such as pools, which are not relevant in the calculation of property valuation in this case (although, for other jurisdictions pool areas may be included in valuation).

With the adoption of GeoAI, valuers no longer need to spend most of their time doing house-to-house inspections. Instead, their tasks may shift to accommodate the use of GIS and remote sensing technologies, validate the vectorized building footprints, and update digitized building boundaries. The cost savings may be re-allocated to the training and procurement of infrastructure to support GeoAI implementation.

4.2 How BFE Models Compare in Terms of Valuation Estimates?

In Table 3, about 4,657 cadastral parcels were valuated using building area inputs from three BFE models. Welch's two sample t-test results show that BFE3 generate valuation estimates that are statistically similar to that of cadastral valuations (p-value=0.8643). In terms of Median Absolute Percentage Error (mdAPE) and Median Percentage Error (mdPE), BFE2 and BFE3 perform better than BFE1 with half of parcels observed to be within 17% of the benchmark (cadastral valuations), which is comparable with the models described in Kok et al. (2017) and twice that of GeoPhy's AVM (Dorigo, 2020).

Table 3. Model comparison based on selected key performance metrics

Model	# Parcels	MAE (ZMK)	mdAPE (%)	mdPE (%)	*p*-value (t-test)
BFE1	4,657	233,754	18	-5	0.0004
BFE2	4,657	233,788	17	-2	0.1341
BFE3	4,657	238,427	17	2	0.8643

In Figure 7, comparison of model performance in terms of mdAPE by residential band or zone, BFE3 clearly outperforms the other two models with the lowest mdAPE in most zones. In general, BFE1 and BFE2 tend to perform poorly in high income residential zones as indicated by higher mdAPE values. That may be attributed to the tendency of semantic segmentation models to underestimate building areas due to tree cover.

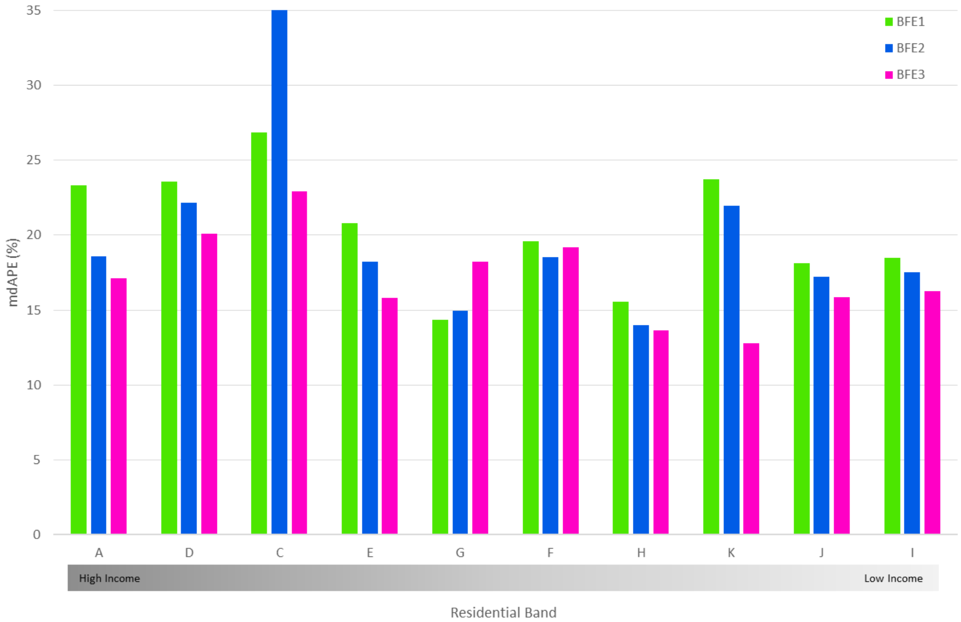

Figure 6. Model performance across different residential zones (bands)

Above figure allows identification of areas that could be subjected to further investigation to improve model performance or assist in prioritizing areas for QA/QC. Editing vectorized building footprints, as generated by GeoAI, is way much easier than digitizing building areas from scratch. Despite the presence of some errors, GeoAI as applied to building footprint extraction will save tax valuation agencies a huge amount of time and financial resources compared to strong reliance on house-to-house surveys.

4.3 Summary

The case study of Lusaka City demonstrated the potential of GeoAI in making simplified tax valuation in developing economies more efficient and cost effective. Contrary to examples of AI application in developed economies where AI methods are introduced as "replacement or alternative" to existing valuation methods, GeoAI could play a unique role in developing economies as an "assistive" tool to speed up the generation of inputs to simplified valuation at a fraction of costs of physical inspections. MLG continues to work closely with LCC to further enhance the GeoAI solution, for example, by capturing the different levels of building completion that will be incorporated in the property valuation formula.

5. CONCLUSION

This paper argues that the use of GeoAI could improve property valuation in developing economies by providing up-to-date inputs to valuation process in a more efficient and cost-effective manner. As demonstrated by the case study in Lusaka, GeoAI—the combined application of AI, GIS, remote sensing, and big data technologies in solving problems—has the potential in speeding up the simplified valuation process in a more efficient and cost-effective manner. GeoAI has proven to be effective in extracting building footprints from UAV orthophotos, resulting in valuation estimates that were statistically similar to the benchmark, and accuracy comparable with that of other studies (Kok et al., 2017). All of these at a fraction of the time and cost required to conduct house-to-house surveys. The authors think that the case study, in some form or another, can be applied to other jurisdictions.

There is growing literature on AI application in property valuation, even outside the confines of tax assessment and administration (Abidoye et al., 2021; Wang & Li, 2019). In developed economies, this pattern is moving towards the incorporation of AI as a "replacement or alternative" to existing valuation methods—a move from equation-based to AI-based valuation (Gloudemans & Sanderson, 2021). Such pattern is nearly absent for developing economies mainly due to lack of data and expertise.

Fortunately for developing economies, there is also a growing trend in GeoAI for property valuation, and land administration in general (Bennett et al., 2021; Koeva et al., 2021). Such trend is characterized by increasing use of AI in remote sensing, the prevalence of high spatial resolution images from satellites and UAVs, the growing sophistication of GIS tools that integrates DL algorithms, and adoption of big data platforms such as cloud computing.

Barriers remain that need to be addressed for AI adoption, such as predictive accuracy and explainability so valuation estimates can be defended in the face of objections (McCluskey et al., 2012; Pipitone, 2022). However, recently known AI adoption in valuation (i.e., the case of PVSC in Canada) suggests that those issues can be addressed if there is a commitment towards adoption (Gloudemans & Sanderson, 2021; Goldfarb et al., 2021). Such commitment will involve management buy-in, acquisition of technical expertise through consultants and/or training of staff, procurement of needed technology solutions, and changes in validation procedures to ensure AI methods meet the standards (Gloudemans & Sanderson, 2021; Goldfarb et al., 2021).

Therefore, the authors support the vision towards the development of standards on the use of AI in property valuation (Abidoye et al., 2021; Gloudemans & Sanderson, 2021). Such standards will not only provide valuers in developed economies additional tools for valuation, but also guide the use of GeoAI to complement existing valuation processes in developing economies. In this context, professional organizations could play a key role in driving the adoption of AI for valuation through standards, education, training, and so on (Abidoye et al., 2021).

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