

Received:

15 April 2016

Revised:

30 August 2016

Accepted:

29 September 2016

Heliyon 2 (2016) e00174



CrossMark

High resolution mapping of development in the wildland-urban interface using object based image extraction

Michael D. Caggiano^{a,*}, Wade T. Tinkham^a, Chad Hoffman^a, Antony S. Cheng^a, Todd J. Hawbaker^b

^a Forestry and Rangeland Stewardship, Colorado State University, Fort Collins, CO 80523, USA

^b US Geological Survey, PO Box 25046, MS 507 Denver CO 80225, USA

* Corresponding author.

E-mail address: Michael.caggiano@colostate.edu (M.D. Caggiano).

Abstract

The wildland-urban interface (WUI), the area where human development encroaches on undeveloped land, is expanding throughout the western United States resulting in increased wildfire risk to homes and communities. Although census based mapping efforts have provided insights into the pattern of development and expansion of the WUI at regional and national scales, these approaches do not provide sufficient detail for fine-scale fire and emergency management planning, which requires maps of individual building locations. Although fine-scale maps of the WUI have been developed, they are often limited in their spatial extent, have unknown accuracies and biases, and are costly to update over time. In this paper we assess a semi-automated Object Based Image Analysis (OBIA) approach that utilizes 4-band multispectral National Aerial Image Program (NAIP) imagery for the detection of individual buildings within the WUI. We evaluate this approach by comparing the accuracy and overall quality of extracted buildings to a building footprint control dataset. In addition, we assessed the effects of buffer distance, topographic conditions, and building characteristics on the accuracy and quality of building extraction. The overall accuracy and quality of our approach was positively related to buffer distance, with accuracies ranging from 50 to 95% for buffer distances from 0 to 100 m. Our results also

indicate that building detection was sensitive to building size, with smaller outbuildings (footprints less than 75 m²) having detection rates below 80% and larger residential buildings having detection rates above 90%. These findings demonstrate that this approach can successfully identify buildings in the WUI in diverse landscapes while achieving high accuracies at buffer distances appropriate for most fire management applications while overcoming cost and time constraints associated with traditional approaches. This study is unique in that it evaluates the ability of an OBIA approach to extract highly detailed data on building locations in a WUI setting.

Keywords: Environmental science, Geography

1. Introduction

The Wildland Urban Interface (WUI) is described as the geographic area where human development encroaches upon and intermixes with wildland vegetation (Stewart et al., 2009). Over the last several decades, the spread of development into wildlands has expanded the extent of WUI across the United States resulting in increased concern related to land use planning, habitat conservation, ecosystem services provided by forests, and community protection from wildfire hazards. This study primarily examines the WUI in the context of wildfire hazard management. Of particular concern to many land managers and national policy-makers over the last decade has been the increase in the number of wildfires at the WUI, which has been attributed to the buildup of wildland fuels, climate change, and increasing development (Keeley et al., 1999; Westerling et al., 2006; Theobald and Romme, 2007). The increased number of WUI fires have resulted in greater numbers of firefighter fatalities, home losses, and federal expenditures (Mell et al., 2010; Gude et al., 2013), leading to policies that highlight the need for improved land use planning, community scale fire mitigation, and effective fire response. One tool that has been identified as a key to improving WUI wildfire management, planning, and response are detailed maps that identify building locations and other community values at risk (Calkin et al., 2011).

At the national scale in the United States, WUI mapping efforts that facilitate regional and temporal comparisons have been conducted using census block data because of their standardized methodology and wide spread availability (Radeloff et al., 2005; Theobald and Romme 2007; Hammer et al., 2007). However, due to the conversion of point to zonal data in the development of census data, census based maps have several limitations, including variable precision across space, and an increased likelihood of excluding isolated buildings and scattered low density development (Bar-Massada et al., 2013; Clark et al., 2009; Platt, 2010). Theobald and Romme (2007) attempted to address some of these limitations through the use of daysemteric techniques which remove undeveloped land prior to calculating

building density; however, such approaches still suffer from the modifiable areal unit problem, which introduces a statistical bias by aggregating point based data into zones of varying sizes (Openshaw and Openshaw, 1984). Even if potential biases associated with the use of census data were overcome, these approaches are still limited for fine scale fire and emergency service planning and operations because they do not provide spatial location data for values at risk at an appropriate scale for many fire management applications, nor do they include other outbuildings and auxiliary structures that represent additional values at risk in the WUI (Theobald and Romme, 2007).

Alternatively, WUI maps that include the spatial locations of buildings can be developed through several manual approaches including digitizing building footprints from municipal records or aerial imagery (Lowell et al., 2010), collecting building locations with GPS units (Calkin et al., 2011), or using building location proxies such as addresses or parcel centroids (Platt, 2010; Calkin et al., 2011). The increased spatial detail and ability to identify isolated buildings and low-density development by using these approaches avoids several weaknesses of census based WUI maps (Calkin et al., 2011; Bar-Massada et al., 2013). Furthermore, since building-based WUI maps are often derived from frequently updated remotely sensed or aerial imagery, they provide additional temporal resolution compared to census based maps. The increased spatial and temporal data provided by building-based WUI maps makes them ideal tools for many wildfire management applications, including: community-scale wildfire planning, fuel treatment prioritization, suppression resource allocation decisions, and post wildfire home destruction studies during wildfire incidents (Theobald and Romme, 2007; Platt, 2010; Maranghides and Mell, 2011; Syphard et al., 2012; Bar-Massada et al., 2013; Alexandre et al., 2015). Building-based maps can also provide the level of detail required for other land management and emergency service applications (Bar-Massada et al., 2013). Despite these advantages, building-based WUI maps can have limited spatial extents due to the time and effort required for development, and can potentially reduce accuracy if created from parcel centroids or address data (Platt, 2012). Furthermore, if aggregating data at broader scales, the use of multiple sources can lead to incompleteness, lack of standardization, and methodological uncertainty (Lowell et al., 2010). However, newer technologies and standardized techniques that can process data over large spatial extents hold promise for overcoming some of the current limitations for producing and maintaining building-based WUI maps.

Advances in computer technology, earth observation sensors, and Geographic Information Systems (GIS) sciences over the last several decades have led to the development of Object Based Image Analysis (OBIA) methods. These methods include both automated and semi-automated methods, and utilize remote sensing,

GIS technology, high resolution imagery, and image classification algorithms to extract discrete objects, such as buildings, roads, and developed areas.

As opposed to traditional remote sensing approaches which classify individual pixels based on their spectral signatures alone, OBIA methods attempt to identify discrete objects by examining the spatial and spectral associations of groups of pixels with unique characteristics (e.g., shape, color, reflectance, texture) (Hay and Castilla, 2006). Object Based Image Analysis methods are being used with increasing frequency for a variety of natural resource management applications (Blaschke, 2010; Falkowski et al., 2009; Sofia et al., 2014,) and in urban development assessment (Freire et al., 2014; Tiede et al., 2010; Huang et al., 2014; Han et al., 2015). While OBIA methods have been used to map the general pattern of WUI development (Platt, 2012), and building locations in other areas (cite Tiede et al., 2010), OBIA has yet to be used or evaluated for its ability to extract specific building locations across large and diverse WUI landscapes, nor has it been evaluated against a municipally produced control dataset. Object Based Image Analysis methods have the potential to advance WUI mapping by improving the efficiency of creating highly detailed building-based maps across large spatial extents while providing a consistent methodology and accuracies similar to human interpretation (Lang, 2008). Automated OBIA approaches can be more efficient because they do not require a human interpreter, but image processing algorithms have to be developed and accuracy can sometimes be less than desirable. Semi-automated OBIA approaches combine automated image processing algorithms followed by human interpretation for improved quality control. Semi-automated approaches can increase accuracy and confidence in data and can take less time than either manual or automated approaches, because the additional time for quality control is often less than the time required to refine algorithms for unique applications. Ultimately, the strengths and weaknesses of different approaches will vary for different applications, and are influenced by the characteristics of the objects of concern, their pattern and prevalence on the landscape, image quality, spectral resolution, and environmental conditions (Turner and Gardner, 1991).

The objective of this study is to evaluate the potential for using an OBIA approach for the detection of individual buildings within the WUI. We evaluate this approach by comparing the accuracy and overall quality of extracted buildings to county maintained building footprint control data. Specifically, this study examined: (1) the influence of semi-automated and automated OBIA methods on extraction accuracy and quality, (2) how error and accuracy is related to the distance between extracted buildings and control building footprints, (3) the influence of environmental characteristics, including topography and vegetation on building detection, and (4) specific errors that occurred during the extraction process and possible reasons they occurred. We conclude with a discussion of

potential applications, limitations, and future areas of research related to using OBIA methods in WUI mapping.

2. Methods

For this study, we choose four counties (Larimer, Boulder, Gilpin, and Clear Creek) in northern Colorado, USA. These four counties contain a large area of WUI (Radeloff et al., 2005), that span a diverse range of land uses, terrain, vegetation types, housing densities, and patterns of development, likely representative of WUI conditions across the western United States. This area spans elevations ranging from 1,500 to 2,800 meters, and includes multiple vegetation types including short grass prairie, shrub lands, dry and mesic conifer forests commonly found in the Rocky Mountains of the Western United States. Home density in our study area varied from 3 to 170 buildings per km², spanning a rural urban gradient that encompasses interface, intermix, and occluded communities. In addition, these four counties had building footprint data that was manually digitized from high resolution imagery and updated using building permit data. Within these four counties we randomly selected ten 3.75 by 3.75 minute quarter quadrangles (approximately 5.28 km by 6.94 km), and clipped the corresponding county building footprints (Fig. 1). Across the ten randomly selected quadrangles there were a total of 12,758 building footprints, at an average

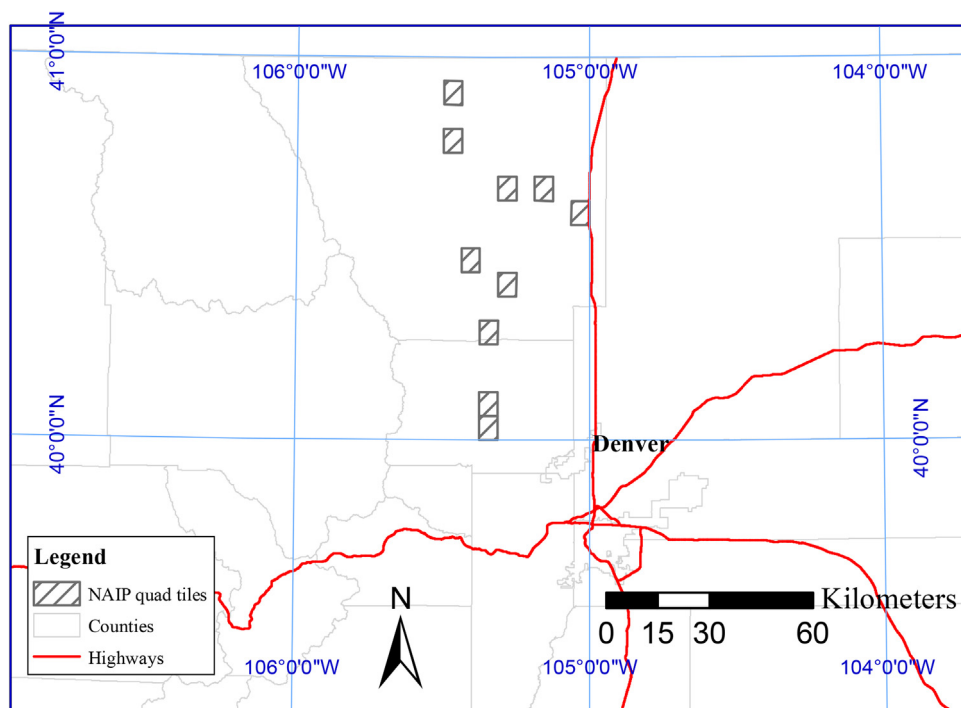


Fig. 1. Basemap of the study area and the ten randomly selected National Aerial Image Program (NAIP) quadrangles used in the evaluation.

density of 35 buildings per square kilometer. The least developed quadrangle contained 101 building footprints and the most developed contained 6,282 building footprints. For each of the ten quadrangles, we also downloaded the corresponding 4-band (red, green, blue, and near infrared bands) multispectral National Aerial Image Program (NAIP) imagery tiles. The NAIP imagery used in this study was taken in 2013 and made available to the public in 2014. We utilized NAIP imagery in our study because it is a freely available standardized product for the western United States, has a fairly fine scale resolution (0.5 to 1.0 m), and has been successfully utilized in other OBIA applications (Garritty et al., 2008; Smith et al., 2008). We used Feature Analyst software (Textron Systems 2015), a third party extension for ArcGIS Desktop (ESRI, 2011), to extract individual building locations from the NAIP imagery tiles, corresponding to our ten randomly selected quadrangles. Feature Analyst is a third party extension for ArcGIS Desktop (ESRI, 2011) that uses a customizable semi-automated machine learning classification approach (Opitz and Blundell, 2008) to extract individual features from imagery. This software was chosen in part due to its ease of use, which is an important consideration for fire and emergency service professionals whom are developing individual-based WUI maps.

To initialize the OBIA processes, we digitized an initial training set of 5–10 representative building footprints in each NAIP image tile that captured a range of building roof colors, sizes, shapes, shadows, and spatial associations present. We then input the training set along with default input parameters to extract an initial set of objects from each image. For all semi-automated iterations, we used the default input parameters for manmade objects (including buildings), all four bands present in the NAIP imagery, a bulls-eye representation, pattern and a 30-pixel window. The default pattern was used to assist with reproducibility and help ensure the extraction could utilize both the shared and unique characteristics of the training set features to find similar objects in the imagery. Opitz and Blundell (2008) provide a more detailed description of how objects of concern guide the selection of input parameters in Feature Analyst. The dataset resulting from the initial extraction included those training set buildings we had originally identified plus additional features that shared similar spatial and spectral characteristics.

Following the initial feature extraction processes, we created a correction dataset by randomly selecting four to six developed and undeveloped areas in each tile (representing approximately 25% of the total area) and identified ten to twenty correctly and incorrectly identified features. This data was then used to supplement the original training set by refining the spatial and spectral characteristics of the buildings during a second processing iteration. After reviewing the extracted features from the second iteration an additional correction dataset was developed and a third iteration was performed. This processes was repeated an additional time for a total of four semi-automated iterations. After extracting building locations

from the four semi-automated iterations, we created the fifth dataset by visually inspecting the results of the fourth iteration and manually added any missed building and removed any incorrectly identified objects. Fig. 2 highlights this iterative process and shows example outputs from the first, second, and manual iterations. Depending on quality requirements for a particular application, users can conduct different levels of quality control on the final dataset by spending more or less time correcting and adjusting features to improve accuracy. Depending on the chosen amount of quality control, this process is likely less intensive than traditional manual digitizing because of its ability to focus the user on areas that require additional attention. In our process, the rapid manual scan of a single quadrangle took about 10 minutes as compared to the 30 minutes we estimate it would have taken for traditional manual digitization. The extracted feature polygons from each of the five iterations were converted to centroids to simplify further analysis, reduce computational requirements, and minimize data storage.

For each of the five data sets we calculated the distance between the edge of each control building footprint and the nearest extracted feature centroid, then for each extracted feature centroid we measured the distance to the edge of the nearest control building footprint polygon; separation distances were then assigned to control and extracted feature datasets respectively. The separation, or buffer distances were used to determine accurately identified buildings, missed buildings, and incorrectly identified objects. Accurately identified buildings or true positives (TP) were those control building footprints that had at least one extracted feature centroid within a selected buffer distance. Omitted errors or false negatives (FN)

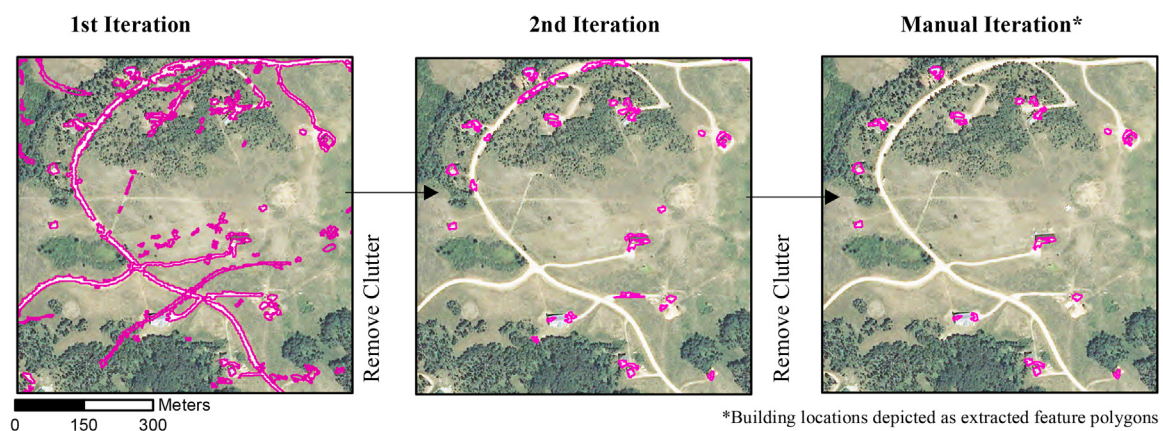


Fig. 2. Extracting buildings in the wildland urban interface using an object based image analysis. The evaluated method uses an iterative process that starts with a user defined training set and user defined algorithms to produce an initial dataset of objects interpreted as buildings (pink polygons). It then uses manual intermediate steps to identify a secondary training set of correctly and incorrectly identified objects to refine object detection algorithms for subsequent outputs. Lastly, a user can conduct quality control by manually adding missed buildings or removing incorrectly identified buildings in the final dataset.

occurred when control building footprints that did not have at least one extracted feature within the selected buffer distance. Commission errors or false positives (FP) were those extracted feature centroids that did not fall within the selected buffer distance around the control building footprints. Fig. 3A provides an example of building footprint polygons, associated extracted features, and their separation distances. In addition to estimating the accuracy, omission and commission errors we also estimated an overall Quality Index (Eq. 1), which cumulatively accounts for accurately identified features, commission errors, and omission errors providing a relativized index of agreement ranging from 0 for complete disagreement to 1 for perfect agreement (Heipke et al., 1997).

$$\text{Quality Index} = \text{TP}/(\text{TP} + \text{FP} + \text{FN}) \quad (1)$$

For each iteration we calculated accuracy, error (omission and commission), and Quality Index (Fig. 4) using a representative 30 m buffer distance because it maintains both high levels of accuracy and contains an appropriate level of detail relative to most fire management applications (Calkin et al., 2011).

After determining which dataset had the highest Quality Index, we examined the effect of different buffer distances (0, 10, 20, 30, 40, 60, 80, 100 m) that span a range of suggested precisions in fire management on accuracy and errors (Calkin et al., 2011). This scale of analysis as depicted in Fig. 3B is important because specific applications will have different requirements. For example, an emergency evacuation may need to locate homes to within 50 meters to know where to send emergency service personnel, while a land manager wanting to estimate how many homes would be protected by a community fuel break may only need to locate homes to within 100 meters. Evaluating multiple scales allowed a building to be

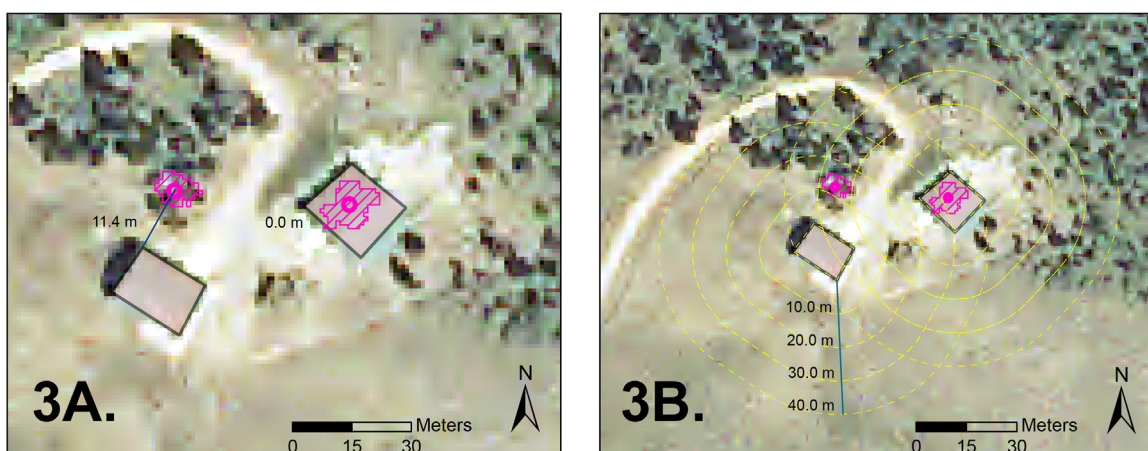


Fig. 3. 3A) Separation distance between the control building footprint (solid polygon), and the extracted feature centroid (circle within hatched polygon) used to identify accurately identified features and extraction errors. 3B) Buffers around control building footprints (solid polygon) are used to assess agreement with extracted feature centroid (circle within hatched polygon) at different scales.

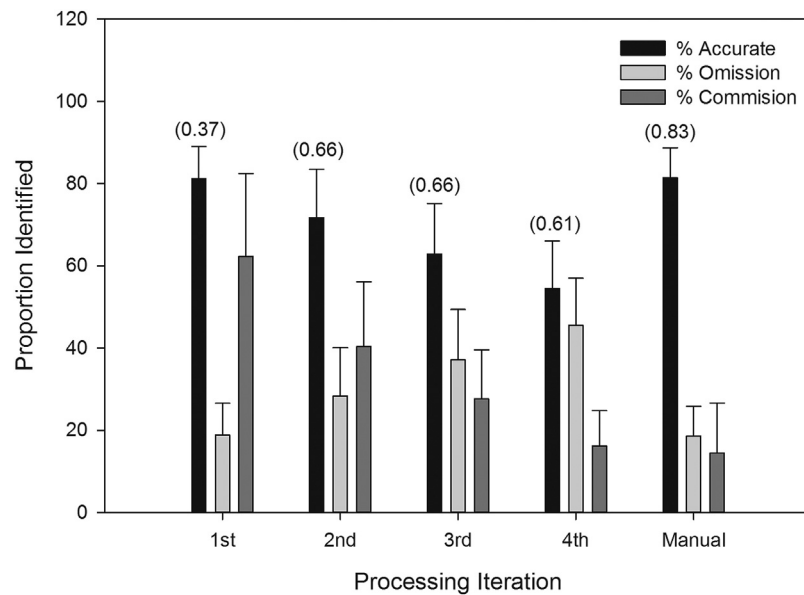


Fig. 4. Accuracy, omission error, and commission error between control buildings and extracted features during each iteration of the Object Based Image Analysis extraction. The error bars represent the 95th confidence interval between samples, and the composite quality index is shown in parenthesis above the error bars.

considered accurately identified using a large buffer distance, but register as an omission error using a smaller buffer distance. In Fig. 3B, the building on the left (with the nearest extracted centroid 11.4 m away) would be considered accurately identified using a 20 meter buffer, but if using a 10 meter buffer, the building would be considered an omitted feature, and the extracted feature (11.4 m away) would then be considered a commission error. The building on the right would be considered accurately identified at all buffer distances. After assessing the influence of buffer distances on extraction accuracy and overall quality, we examined how broad scale environmental factors influenced the extraction.

Lastly, we examined the influence of building size, building density, vegetative properties, and topographic characteristics on extraction accuracy. The effect of building size on accuracy and error was estimated by classifying building sizes into 25 m² bins from 0 to 275 m² and larger, and then calculating the accuracy for each group using a 30 m buffer distance. To assess the influence of building density, vegetative properties, and topographic characteristics on accuracy we estimated the building density, vegetation type, canopy cover, fuel type, slope, aspect, and elevation, for each of the control building footprints. Local building density was calculated for each extracted feature in the control dataset using a circular 500 m neighborhood. All other variables were sourced from the 2011 National Elevation Database (30 m resolution; Homer et al., 2015) and data from the LANDFIRE Project (Rollins, 2009). The range in accuracies within classes for each

environmental characteristic were compared against each other and analyzed for trends and variability.

Finally, we attempted to qualitatively identify the causes of omission and commission errors by randomly sampling 10% of the errors and noting the probable cause of each error. These descriptive error classifications are presented in the discussion along with the other methodological, control data, and imagery related limitations.

3. Results

We found that all iterations correctly identified greater than 50% of all buildings using a 30 m buffer distance, with the initial semi-automated iteration achieving the greatest overall accuracy (Fig. 4). Although the 1st iteration had the greatest overall accuracy, and accordingly the lowest omission error, this data set also had the highest commission error and a lower overall quality index (0.37). Commission errors decreased with subsequent iterations, while the quality index varied between 0.61 and 0.66 for subsequent iterations (Fig. 4). The incorporation of a rapid manual iteration resulted in 81% of all homes being correctly identified, and omission and commission errors of 19 and 15% respectively. The Quality Index was greatest following the inclusion of a manual iteration to 0.83. Suggesting, that the inclusion of a rapid manual iteration results in the best overall performance.

We found that the overall accuracy, and Quality Index were positively related to buffer distance, while both omission and commission errors were negatively related to buffer distance (Fig. 5). At the 0 m buffer distance overall accuracy, omission error, commission error and the quality index were 50.1%, 49.9%, 34.1%, and 0.46 respectively. For the largest buffer distance evaluated (100 m), the overall accuracy (95.3%) and quality index (0.96) were the greatest while omission error (4.7%), commission error (3.1%) were the smallest. In addition to increased overall accuracies and quality, we also found decreased variability between the ten randomly selected quadrangles at larger buffer distances.

Our results also indicated that that extraction accuracy varied by building size (Fig. 6). In general, overall accuracy was positively related to building size, with the two smallest size classes (less than 50 m²) having accuracies around 70% and larger buildings (greater than 150 m²) having accuracies of over 90%. With the exception of canopy cover, which we observed to have reduced our ability to extract buildings, and in turn decreased our accuracy, we found no discernable trends in terms of accuracy, omission and commission errors related to any of the other landscape scale characteristics we tested for including; building density, slope, aspect, elevation, and vegetation type.

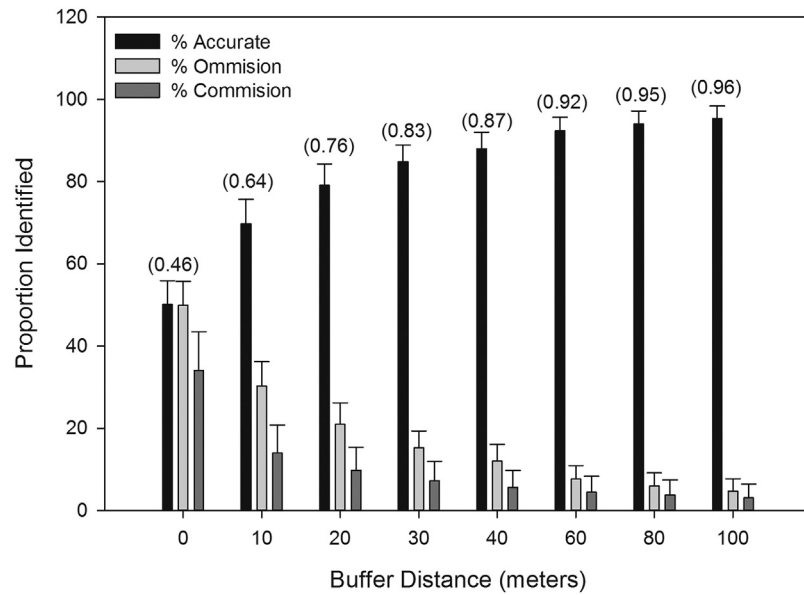


Fig. 5. Accuracy, omission error, and commission error between control buildings and extracted features produced from the final manual iteration. The error bars represent the 95th confidence interval between samples, and the composite quality index is shown in parenthesis above the error bars.

4. Discussion

The objective of this study was to assess a semi-automated Object Based Image Analysis (OBIA) approach that utilizes 4-band multispectral National Aerial Image Program (NAIP) imagery for the detection of individual buildings within the WUI

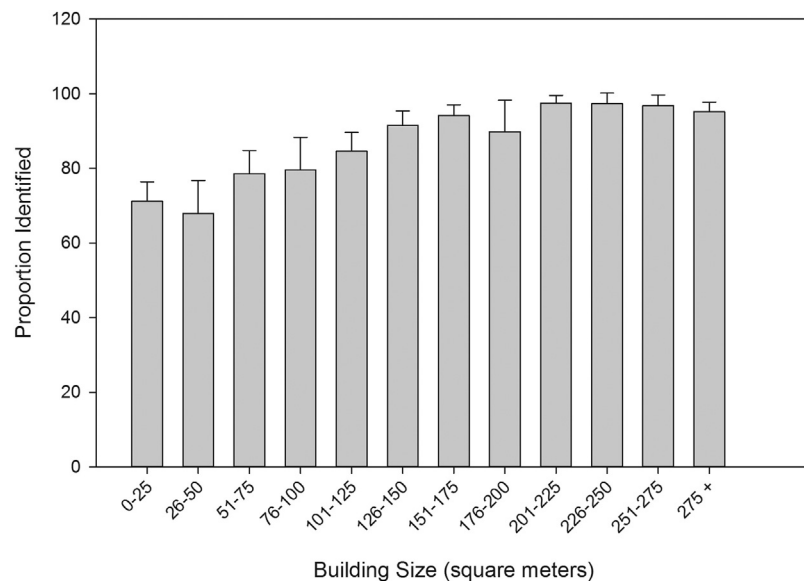


Fig. 6. Extraction accuracy for different building sizes, classified into 25 m² bins, using a representative 30 m buffer.

in Northern Colorado. We evaluated this approach through comparisons with county maintained building footprint control data and additional analyses of the effects of buffer distance, and the topographic and building characteristics on the accuracy and quality of building extraction. Our results indicated that all iterations correctly extracted at least 50% of all buildings, with a 30 m buffer distance, but that overall quality and accuracy were greater when at least two iterations were included. Our results also indicated that extraction accuracy and quality are dependent upon the selected buffer distance. Although there are no accepted standards for an appropriate buffer distance in WUI mapping, Calkin et al. (2011) suggested that 100 m would be appropriate for most fire management applications. Given this buffer distance, our manual dataset had a Quality Index of 0.96, accurately identified 95% of all buildings, and had omission and commission errors below 6%. These results suggest that the inclusion of a manual iteration results in improved quality and accuracy (Freire et al., 2014). Our efforts also show that for mapping buildings in our WUI study area, the semi-automated process can achieve similar accuracies as reported for traditional digitization efforts (Lowell et al., 2010), but with reduced effort. These findings indicate that the use of an OBIA approach holds promise for developing detailed building-based WUI maps across broad scales in support of fire and emergency service operations and planning.

In addition to assessing the overall accuracy and quality of the OBIA approach we also investigated the causes of omission and commission errors. The causes of these two types of errors are important to understand if building-based maps are to be used in operational planning during wildland fire events as these errors could impact the strategic use of resources as well as tactics and strategies during the event. Visual inspection of omission and commission errors indicate that both the selected buffer distance and the size of the target building influenced the overall errors. In cases where a short buffer distance was chosen, buildings that were in close proximity to accurately extracted features were common among the omission errors we subsampled. The final building extraction also omitted a disproportionately high number of small outbuildings and non-residential building, which were sometimes partially obscured by overhanging vegetation. Lowell et al. (2010) also noted the challenge of identifying small buildings obscured by vegetation while digitizing buildings in the WUI. During our final manual iteration, we were able to visually locate many of these smaller buildings; however, decreased accuracies should be expected in areas with dense continuous canopy cover. Commission errors were generally associated with the extraction of natural features such as rivers, and rock outcroppings, and features of the built environment such as roads, vehicles, and shadows. Commission errors that were associated with the natural environment were often caught and removed during the first and second semi-automated iterations. However, errors associated with the built environment often persisted through the semi-automated results and were removed during the

final manual iteration. Most of the omission and commission errors that remained following the manual iteration were often in close proximity (< 100 m) to accurately extracted buildings. Given that the majority of omission and commission errors occurred within a relatively close proximity to the built environment and other buildings, these errors would likely have little impact on most fire and emergency management applications.

We identified several cases where omission and commission errors were associated with the control data set we used. For example, we identified several omission errors that occurred in partially constructed subdivisions where the control dataset indicated there was a building, but there was no building present in the imagery. [Rutzinger et al. \(2006\)](#) suggested this type of error could be due to temporal scale mismatches inherent in datasets created at different times. While this could be partially mitigated by regularly extracting buildings from the most recently acquired imagery, these errors suggest the potential for decreasing accuracy over time as new buildings are constructed, a temporal limitation inherent in all static geospatial data that represents physical features in dynamic systems. We also found some commission errors resulting from buildings which appeared to have been accurately extracted from the imagery, but were missing from the control dataset. In these cases, it is likely that the county maintained control dataset contained errors and did not fully account for all buildings within its jurisdiction. This could have occurred if a landowner did not apply for a building permit before starting construction, or through a user introduced error while maintaining or updating cadastral data.

For any particular fire and emergency management application, it is critical that practitioners clearly identify accuracy and quality requirements, the appropriate buffer distance, and understand the potential implications of omission and commission errors to ensure that any building-based WUI map is appropriate for their specific need. For example, building-based WUI maps that are to be used for community evacuation planning might be more accepting of omitting smaller nonresidential buildings ([Lowell et al., 2010](#)), but for other applications this might have important implications. Recent research has indicated that small outbuildings within the home ignition zone of larger residential buildings can act as ignition sources ([Cohen, 2000](#); [Maranghides et al., 2015](#)). Depending on the specific application, this study indicates that OBIA approaches hold potential to map individual buildings in similar WUI environments at scales appropriate for many wildfire management and planning related applications.

Although our OBIA approach can extract individual buildings within the WUI with a high level of accuracy, further research could identify additional ways to improve overall accuracy and quality while reducing the need for the manual iteration. As suggested by [Blaschke \(2010\)](#), these improvements might be achieved through

advances in different components of the OBIA process such as improvements to image quality, image segmentation, and spectra discrimination. Higher resolution imagery such as 0.5 m NAIP, and 8-band WorldView II or III imagery with 0.4–2.0 m resolution and additional spectral bands is becoming more widely available and could present a first step in improving OBIA segmentation for differentiating objects on the landscape. Combining advances in image quality with more advanced image segmentation algorithms, such as artificial neural networks, fuzzy set methods, and support vector machines hold potential to further improve OBIA discrimination and the resulting data accuracy (Blaschke, 2010; Hay and Castilla, 2008). Though this study utilized ArcGIS and Feature Analyst software, open source GIS platforms, and other remote sensing product with similar or improved resolution and spectral discrimination may be able to produce similar results. Going beyond identifying the location of buildings centroids, future work may be needed to assess the ability of OBIA methods to assess the degree of overlap between the extracted polygon features and control building footprints, or identify other objects in or characteristics of the WUI environment. For example, OBIA also holds the potential to accurately characterize fine scale environmental features that contribute to the wildfire hazard such as fuel heterogeneity around homes; combining bands into normalized Difference Vegetation Index (NDVI) holds potential to more effectively identify vegetation. As improvements to image resolution and processing ability facilitate the widespread use of OBIA for extraction of different types of features, accuracy assessments should continue to incorporate appropriate object based evaluations that differ from traditional pixel based sampling strategies (Radoux et al., 2008). Further, additional research should be done evaluating accuracy, error and overall quality in different settings and locations, utilizing different software, imagery, and algorithms, using solely automated extractions without manual input, different satellites, and imagery of varying resolutions, the effect of different image band combinations, and the relative contributions of unique bands. Additionally, alternative technologies such as LiDAR, with its ability to penetrate forest canopy, may be able to overcome some limitations of OBIA approaches, and would aid in building identification in areas with heavy canopy cover. Integrating OBIA produced datasets of building locations with LiDAR, cadastral, or other environmental data such as parcels, roads, vegetation, or fuel hazard assessments could further improve both data quality and utility for community planning or other wildfire management applications, leading to a more comprehensive understanding of the spatial arrangement between buildings and their surroundings in coupled social environmental systems.

5. Conclusion

Through our evaluation we demonstrate that OBIA can successfully extract buildings from diverse WUI landscapes while achieving high accuracies at buffer distances appropriate for most fire management application. The approach

overcomes the costly and labor intensive nature associated with building-based digitization, as well as the lack of detail and incomplete building counts associated with some zonal based WUI mapping efforts. Our study which has evaluated an OBIA approach that provides some of the first applications of OBIA in the wildland urban interface that both extract highly detailed building locations, and demonstrates applicability for wildfire management applications. Though the evaluation of the OBIA approach has identified several limitations in need of future study, it still holds potential for contributing to a more complete assessment of hazards, exposures, and vulnerabilities in the WUI when detailed data is unavailable. Leveraging OBIA produced dataset of building locations with other landscape scale datasets can deepen our understanding of the specific pattern of development as well as its implications for wildland fire exposure, which could be used to inform land use planning, hazard assessment, and wildfire management.

Declarations

Author contribution statement

Michael Caggiano: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Chad Hoffman, Wade Tinkham: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Antony Cheng, Todd Hawbaker: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

This work was supported by the Center for Managing Wildland-Urban Interface Fire Risk, a program within the Department of Forest & Rangeland Stewardship at Colorado State University, Fort Collins, Colorado. Funding for the Center comes from the US Department of Agriculture, Forest Service, State and Private Forestry Branch.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Acknowledgements

Additionally, we sincerely thank the three anonymous reviewers for their comments which helped to strengthen the papers methods and discussion. Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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