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ABSTRACT

Building energy audits are time-consuming and labor-intensive. This paper describes a new method using machine learning (ML) techniques on novel data sources (drone images) to improve the identification of building characteristics and retrofit opportunities, and thereby reduce the effort for audits. The new ML method includes: (1) Building footprint extraction using line extraction, polygonization, and polygon-merging, (2) Building envelope extraction using PIX4d modeling software to reconstruct a building 3D model, (3) Visualization tool for viewing images from the 3D model, (4) Window-to-wall ratio (WWR) using state-of-art deep neural network semantic segmentation, (5) Envelope thermal anomaly detection using an unsupervised machine learning clustering algorithm, and (6) Rooftop energy equipment detection based on an object detection algorithm. The testing of this method involved a comparison of additional ML-generated information overlaid on current 'state-of-practice' audit and remote assessment baselines using evaluation metrics: labor time and associated cost, marginal benefits of using ML-generated information in workflows for audits and remote assessments, integration potential with existing processes and tools, and replicability/scalability of the method. In two test buildings in California that had comprehensive drawings and meter data available, the ML method effectively generated a building footprint, envelope, rooftop equipment, WWR, and locations of envelope thermal anomalies. Projected target segments of the ML method are sites with minimal drawings and energy data, and underserved sectors such as multistoried housing, disadvantaged communities, and schools for which the ML method can enable identification of building asset characteristics and prioritization of envelope retrofits and decentralized energy equipment retrofits.

Introduction

Important capital-intensive building energy efficiency measures (EEMs) remain largely unaddressed in today's building energy audit and meter analytics technologies. Two such key EEMs are (1) Envelope retrofits, and (2) Equipment efficiency, installation, and replacement. This gap primarily exists due to limited access to envelope and asset information inputs, and the time and labor required to acquire, process, and assess these data. These EEMs are detailed below.

Envelope retrofits: A building envelope modulates its interaction between the indoor and outdoor environment. It plays an essential role in the building's energy performance, since a third of a typical building's energy use is directed towards indoor heating and cooling requirements (DOE, 2015). However, the identification of energy efficiency measures for envelopes is not typically done because the human and analytical resources to identify these EEMs can be costly, so the return on investment is not well-quantified. There is a lack of physical access to the extents and interior of a building's expansive envelope and absence of automated data acquisition from the envelope to be able to detect envelope anomalies (Harris 2021). Auditors express the reservation that in milder climates envelope EEMs are difficult to detect and may not have economic payback for their services. Hence, auditors tend to spend their limited budget on items that are likely to be more fruitful. However, they note that even in non-mild climate zones (such as ASHRAE climate zones 1-3, and 5-7 in the U.S. shown in Figure 2) where envelope retrofits may have significant benefits, they are not usually conducted due to lack of data and analysis.

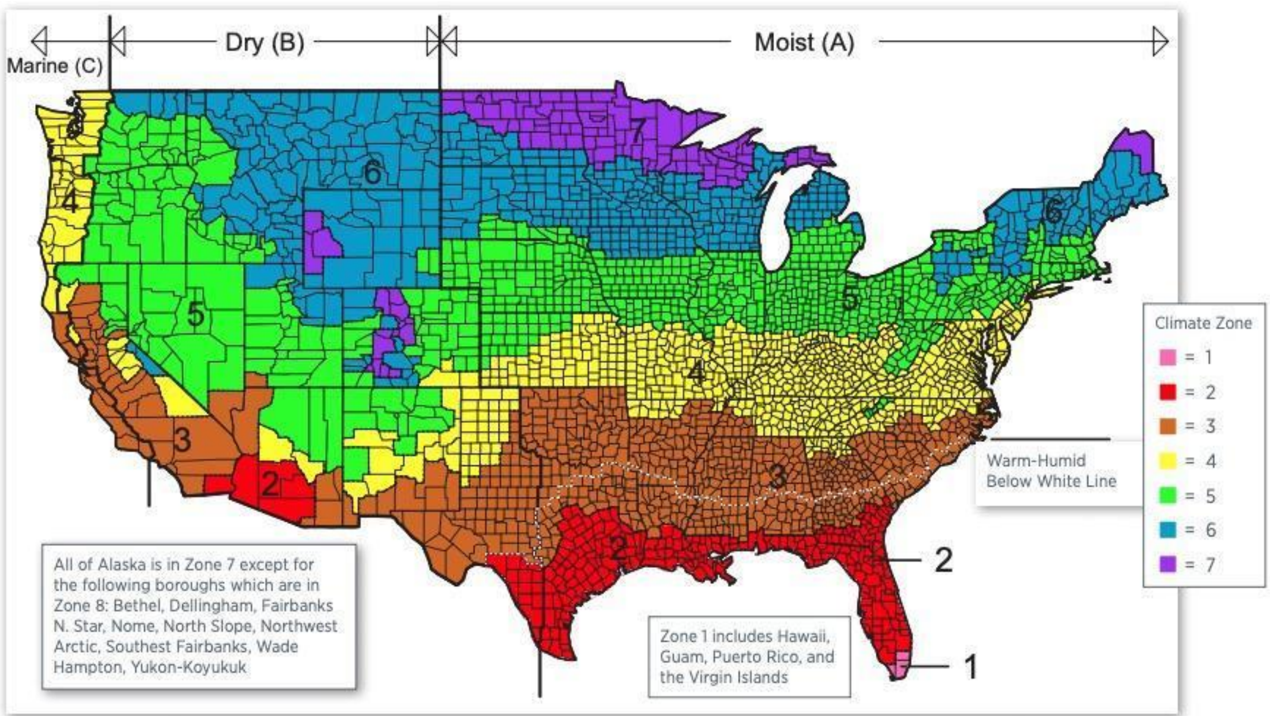

Figure 1. International Energy Conservation Code (IECC) climate regions of the United States. *Source*: ASHRAE, 2011.

Equipment efficiency, installation, and replacement: Heating, ventilation, and cooling (HVAC) is typically the most significant load in a commercial building, and one of the leading causes of inefficient operations (DOE 2015). Remote assessments using smart meter data typically have little information on the installed HVAC assets unless drawings are made available. Hence, the focus of remote assessments is almost entirely on HVAC controls and operations. A gap in audits is to detect the presence and location (and potentially relative size) of rooftop HVAC units (RTUs), as well as solar panels, and solar capacity of the building envelope, both roof and walls, given the emphasis on net zero buildings.

Existing literature has suggested the use of thermography for building performance diagnostic inspections and for accurate envelope characterization (Rakha 2018, El Masri 2020).

The contributions of this work are to develop methods based on machine learning (ML) and novel data sources to improve identification of building characteristics and energy efficiency opportunities. An unmanned aerial vehicle (UAV) was used to capture thermal and red/green/blue (RGB) images of buildings, and novel ML algorithms were developed and applied to extract useful building asset information and energy efficiency opportunities from these images. The new ML methods were compared against existing audit and remote assessment approaches using evaluation metrics. Primary evaluation metrics included labor time and associated cost, and marginal benefits of using ML-generated outputs. Secondary evaluation metrics included potential integration with existing workflows and tools, and process replicability.

Through the new ML methods, five building parameters were automatedly or semi-automatedly extracted, i.e., building footprint, building envelope, window-to-wall ratio (WWR), envelope thermal anomalies, and rooftop assets/equipment.

The objective of this study was to derive scalable data-driven techniques for asset identification and detecting potential thermal anomalies and demonstrate any marginal benefits of this ML method developed by incorporating the outputs it generated with the results of traditional in-person audits and remote assessments. Testing was conducted on two commercial buildings in California.

Methodology

A five-step approach was used to capture data from two test sites, develop and use ML algorithms, and integrate and compare the new method with audits and remote assessments, as described below:

(1) Selected test sites and developed and implemented a field plan for the unmanned aerial vehicles (UAVs): Selected and obtained permits for two medium sized commercial buildings as test sites for UAV flights, and did detailed pre-flight, on-site, and post-flight planning for image and additional data collection from these sites.

(2) Developed and used machine learning (ML) algorithms on the acquired data: Conducted ML-based analysis on the image (RGB and thermal) data and converted it into utilizable file formats and information.

(3) Integrated and compared with audit data analysis (A1, A2): Performed an in-person audit of assets, characteristics, operations and measure opportunities in each building, using the following two sub-steps:

Sub-step A1: Typical ASHRAE Level 2 (L2) audit

- Collected data through a typical request for information (RFI) sent to the buildings' owners/managers: Historical Utility data (12 month electric bills, utility rate structure, Energy Star Portfolio Manager data, 15-minute interval data); On-site generation or storage; Drawings and documentation of site/architectural, mechanical, lighting systems; Occupancy: Estimated occupancy, occupied vs. unoccupied space, tenanted function of space use; HVAC system operations: Sequence of operations, BMS 15-min trends for central plant, zone, and air side equipment; Operations & Maintenance: Lists for HVAC equipment, lighting and ballasts, other equipment, and any existing deficiencies or problems; Past audit or retro-commissioning report: what measures implemented, changes to equipment and controls
- Collected data through in-person visits through observation, instrumentation, and surveys: Site observations were based on typical audit checklists, forms, and tablet-based software tools, including: identification of all major energy consuming systems;

observation of BMS setpoints, sequence of operations, and download of available trend data for the past year with the intent of identifying seasonal variations, any shifts/changes in operations, and if equipment is operating per plan; identification of zones with hot/cold calls, glare problems, or equipment with known maintenance issues through detailed interviews with operators.

- ○ Developed a typical energy audit report package: This comprised annual energy usage data analysis including benchmarking the building performance against Energy Star, EIA's Commercial Building Energy Consumption Survey, or California Commercial End-Use Survey; building energy balance, i.e., the energy use of the building by end use; description of the building, energy using systems, and efficiency measures.

Sub-step A2: Overlaid eQuest simulation on the A1 ASHRAE L2 audit

- ○ Developed a whole building simulation model calibrated to the historical annual energy use of the building and targeted analyses of individual systems compared against the baseline energy balance to estimate savings for the identified measures
- ○ Used ML-generated information from Step 2 to enhance information for each test building as A1'and A2' respectively and compared these to the original standard audit analysis A1 and A2.

(4) Integrated and compared with remote assessments (R1, R2): Performed a remote assessment of energy usage and equipment operations from the two test buildings using the following two sub-steps

Sub-step R1: Reviewed building data, utility data, and building management system (BMS) trend data (as available) with the following activities

- ○ Collected data from the site contact over email and phone calls. Additional information included building envelope specific data to run 'Asset Score' software tool and remote BMS access to retrieve trend data (if available) for HVAC operation.
- ○ Reviewed the obtained data
  - - Utilized Microsoft Excel® to review monthly energy consumption to identify seasonal variation in building energy consumption
  - - Examined the utility provided 15-minute kW interval data for daily, weekly and monthly consumption patterns on OpenEIS and Energy Charting and Metrics (ECAM) tool (Microsoft Excel®) open-source add-on).
  - - Reviewed trend data using the analysis tool in the BMS software (Automated Logic's WebCTRL Building Analytics tool's user interface).
  - - Used U.S. DOE's BETTER tool to assess building performance energy efficiency and Asset Score Tool to assess the physical and structural energy efficiency of test buildings to identify potential retrofits.

Sub-step R2: Overlaid eQuest simulation on the R1 Remote Assessment Study. Used ML-generated information from Step 2 to enhance information for each test building as R1' and R2' respectively, and compared to the original standard remote assessments R1 and R2.

(5) Synthesized the results to determine the marginal cost and benefit of new information from this new ML method: Compared 'standard' analysis from Steps 3 (A1, A2) and 4 (R1, R2) to the enhanced analysis with ML-generated information (A1', A2', R1', R2'). (See Figure 2). Evaluated the efficacy and performance of the new methods overlaid on current remote assessments and traditional in-person audit techniques.

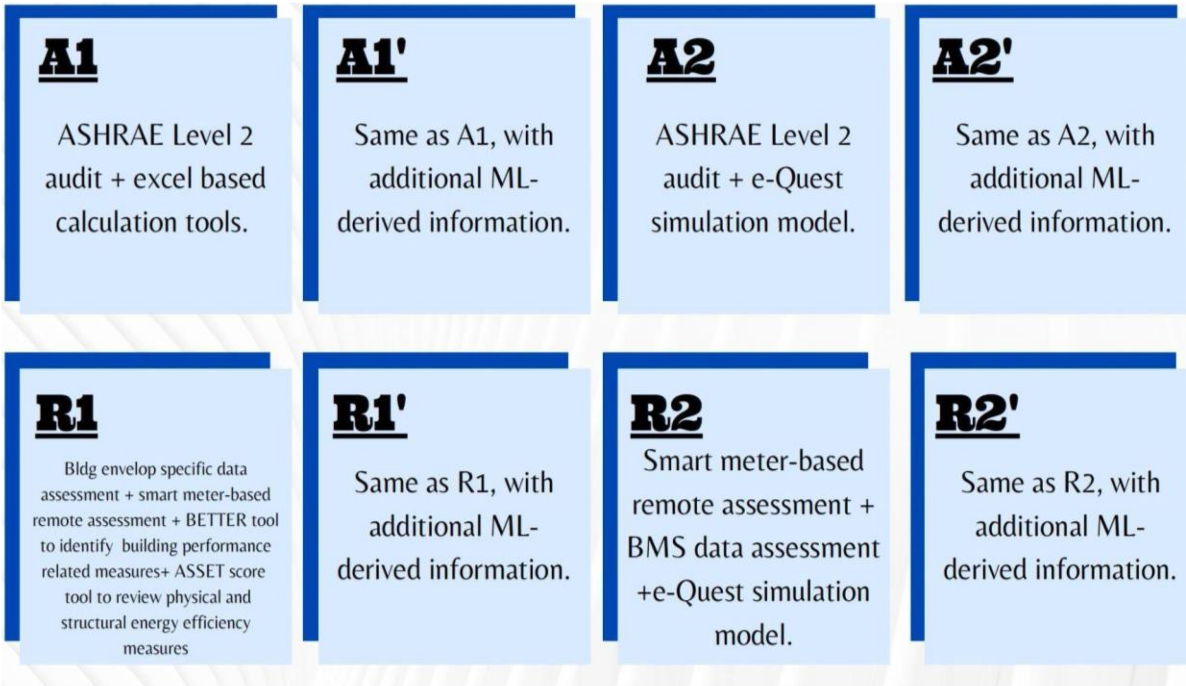

Figure 2. Nomenclature for "standard" analyses, and the "enhanced" analyses using additional ML-generated information

Results

Results of Step 1, Develop and Implement a Field Plan

Two sites were selected (Figure 3) and aerial and oblique RGB and thermal images were acquired, as well as additional data such as outside air temperature.

Site 1: Commercial Office
A 77,361-conditioned square foot office building. Constructed in 1984, it has five floors and a basement (Figure 3a). The building envelope consists of concrete masonry unit walls, double paned windows, and glass exterior doors. The roof of the building is covered with roofing membrane and coated with white reflective paint.

Site 2: Club House
A 63,000 square foot clubhouse. Built in 1925, it has two stories with small offices, a restaurant, a bar, pool, assembly rooms, and a fitness room (Figure 3b). The building has a combination of operable and fixed windows. A large skylight dominates the roof. The building is served by seven 100% outside air package units.

Results of Step 2, Use the machine learning algorithms on the acquired data
The outputs of the machine learning workflows, that were integrated into the audit and remote assessment processes are described below (Figures 4-7).

Figure 3a (left): Commercial Office Site; Figure 3b (right): Club House Site

First, the *building footprint* was extracted using 3 major steps: Line extraction, Polygonization and Polygon-merging, producing a geojson file with coordinates and text. An Aerial 3D Building Reconstruction (A3DBR)[1] (Granderson 2021) building footprint extraction pipeline was developed, using UAV images to construct a building footprint (Figure 4). Details of the analysis pipeline can be found at Granderson et. al 2021.

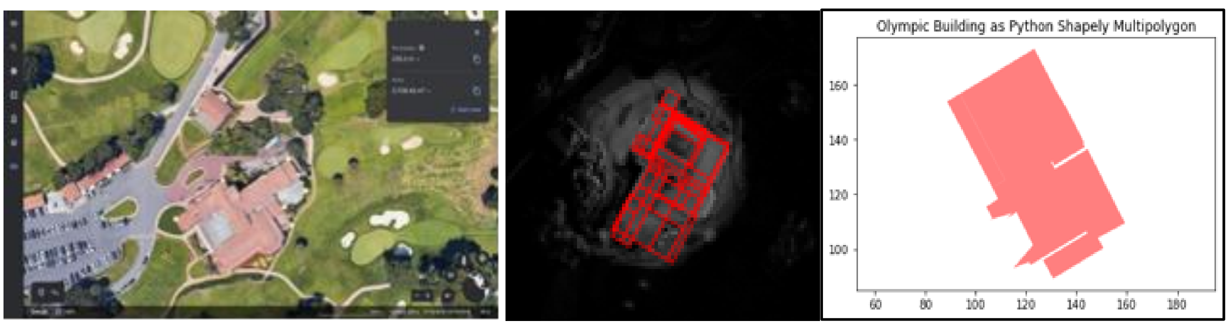

Figure 4. Left: An aerial view of the of Club House Building as seen on Google Earth; Center: an intermediate output in the machine learning process to extract building footprint; Right: ML-derived final footprint output. Note: Coordinates are transposed in plotting, and not visualized in the same orientation.

Further, the *building envelope* was derived from the images to reconstruct a 3D model of the building using PIX4d modeling software. The .las/.obj file was directly exported from the PIX4d software and contained the envelope information of the building as a 3D model.

Next, the *window-to-wall ratio* was extracted. This entailed the construction of a 3D point-cloud of the building, using photogrammetry to detect features that overlapped across images (e.g., lines, edges, corners) in conjunction with GPS data. This 3D model was projected onto a 2D grid, by focus on grid cells corresponding to the building facades that had a very high point density. Next, supervised learning algorithm was trained to detect the windows from the building facades on 2D images. The supervised algorithm employed DeepLabv3+, a state-of-art deep neural network semantic segmentation approach[2]. The output of the windows detection

[1] https://github.com/LBNL-ETA/a3dbr
[2] https://github.com/VainF/DeepLabV3Plus-Pytorch

provided a predicted window mask (Figure 5a). Finally, the facade corner points of the extracted 3D building model were projected onto the RGB UAV camera images that corresponded to the input images with the detected windows. Once the 3D coordinates for the window points were identified on the images, the WWR was computed for each orientation, and output as text files (Figure 5).

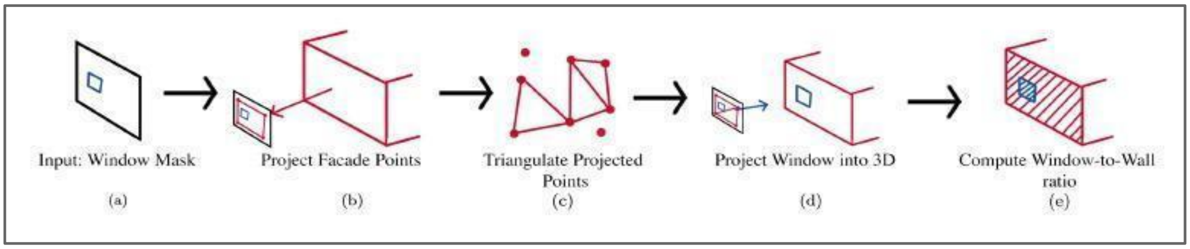

Figure 5a: Flowchart for the WWR extraction process

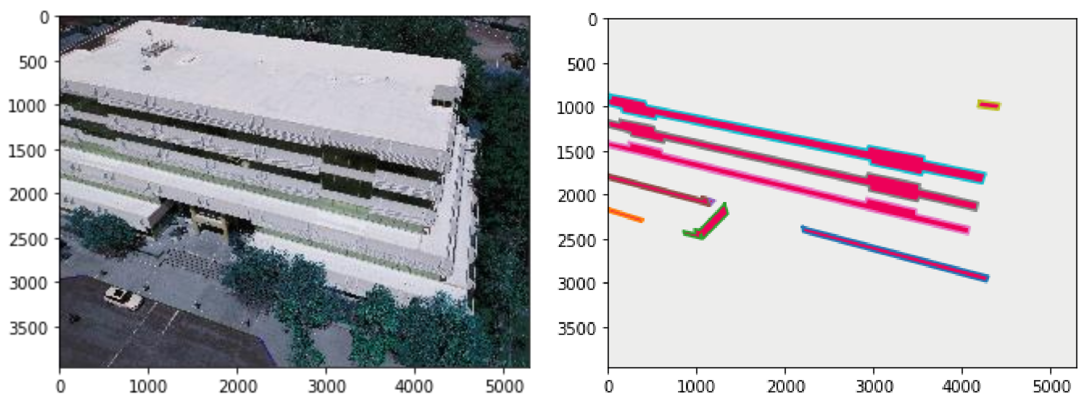

Figure 5b. Window detection outputs used to calculate window-to-wall ratio at the Office building test site

Then, potential *thermal anomalies* were identified. Thermal images (Figure 6a) were converted to images showing the corresponding temperatures (Figure 6b), then a mask was applied from the AutoBFE software pipeline that identified the relevant building areas in the image. Once the building areas were identified, an unsupervised machine learning clustering algorithm (k=16 clusters exhibited optimal detection) was used to segment the temperature on building facades from the rest of the image. (Figure 6c). Finally, the outside air temperature (OAT) on the day was used to set a threshold value (OAT+5 degrees, for example at the office building, 22+5=28 degC) to convert to a binary image using a non-adaptive thresholding technique. The yellow regions were potential anomalies as these parts of the segmented image were above the threshold. A contour was applied to the areas that had a potential thermal anomaly. This was output as jpeg files.

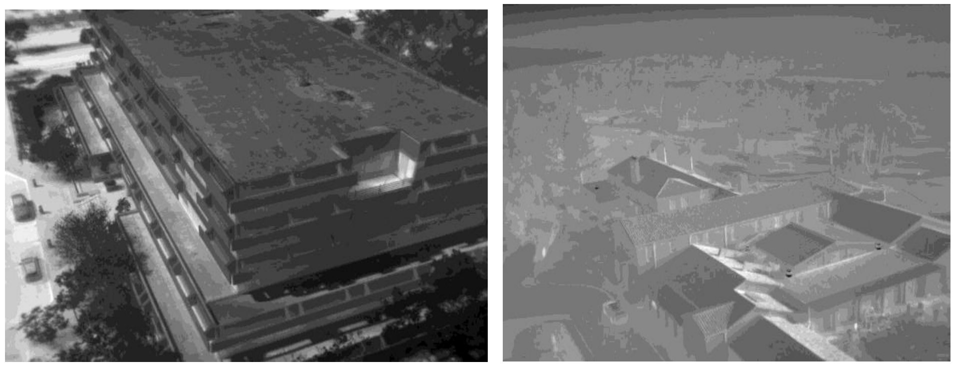

Figure 6a: Thermal image of the two buildings taken from the UAV flights

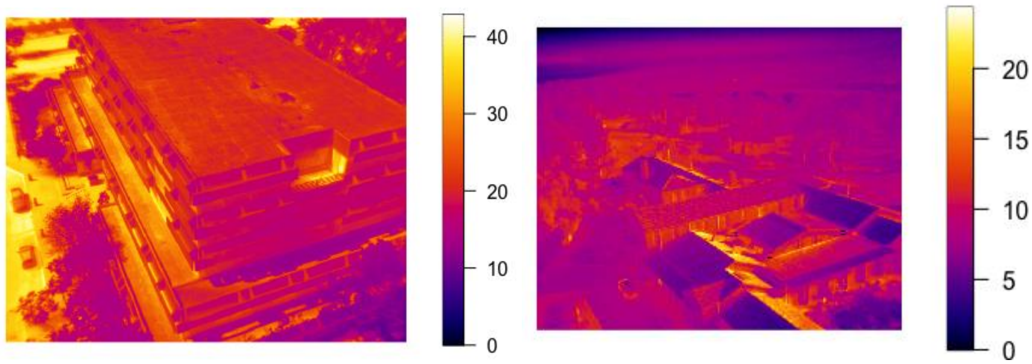

Figure 6b: Temperatures seen in the image in degrees centigrade as a continuous scale

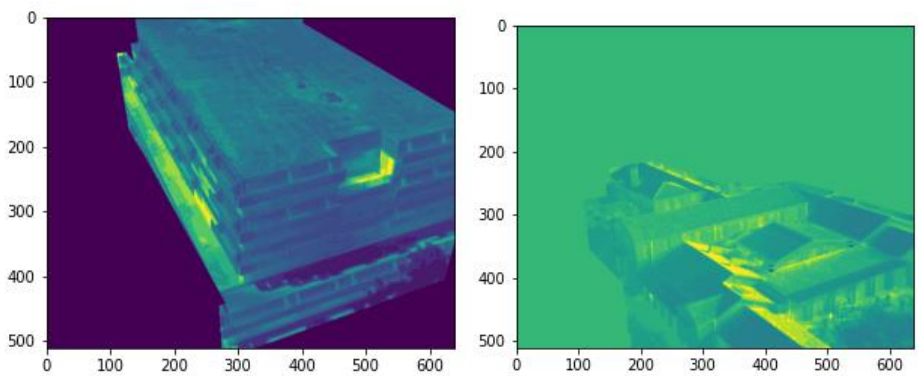

Figure 6c: Use of a clustering algorithm for thermal image segmentation

Finally, *rooftop energy equipment detection* was done. This was based on an object detection algorithm, and output as image with text label. An object detection algorithm was developed using Mask RCNN, a state-of-the-art computer vision algorithm. A model was trained after labeling roof top units (RTUs) on a training dataset and the model used to detect RTUs on the rooftops. (Figure 7). Note that while detecting the number of installed RTUs without requiring a visit to the roof is beneficial, a potential next step in this research may involve extracting sizing, age and other information about the RTUs (see the Conclusion section).

Figure 7. Depicts a rooftop unit detected with 89% certainty based on the Mask-RCNN machine learning algorithm. Left: An RTU labeled by the ML algorithm from the drone aerial image; Right: A zoomed-in image of the same

In addition, semi-automated outputs were extracted as text files from the 3D point cloud model, i.e. floor area measurement, number of floors, and building height.

Results of Step 3, Integrate and compare with audit data analysis

Using the data collected from the site, four outputs were generated from this step as described below. (Note: The outputs of the ASHRAE level 2 (L2) audit have not been included as that was not the contribution of this work).

First, an A1 output was generated from ASHRAE L2 Audit and EEM-specific calculations. Note that an A1'output was not generated since the high-level A1 methodology did not have a framework to incorporate outputs such as WWR or infiltration (however the footprint from the drawings was cross-checked with the ML-derived information). Next, an A2 output was generated using eQuest modeling-based calculations overlaid on the ASHRAE L2 Audit. Finally, an A2'output was generated by augmenting the A2 output with ML-derived information. The savings summary was then revised utilizing the ML-derived information. The ML-augmented audit workflow (Figure 8) and savings summary were assessed to determine what, if any, marginal benefits were obtained. These audit outputs are shown in Table 2.

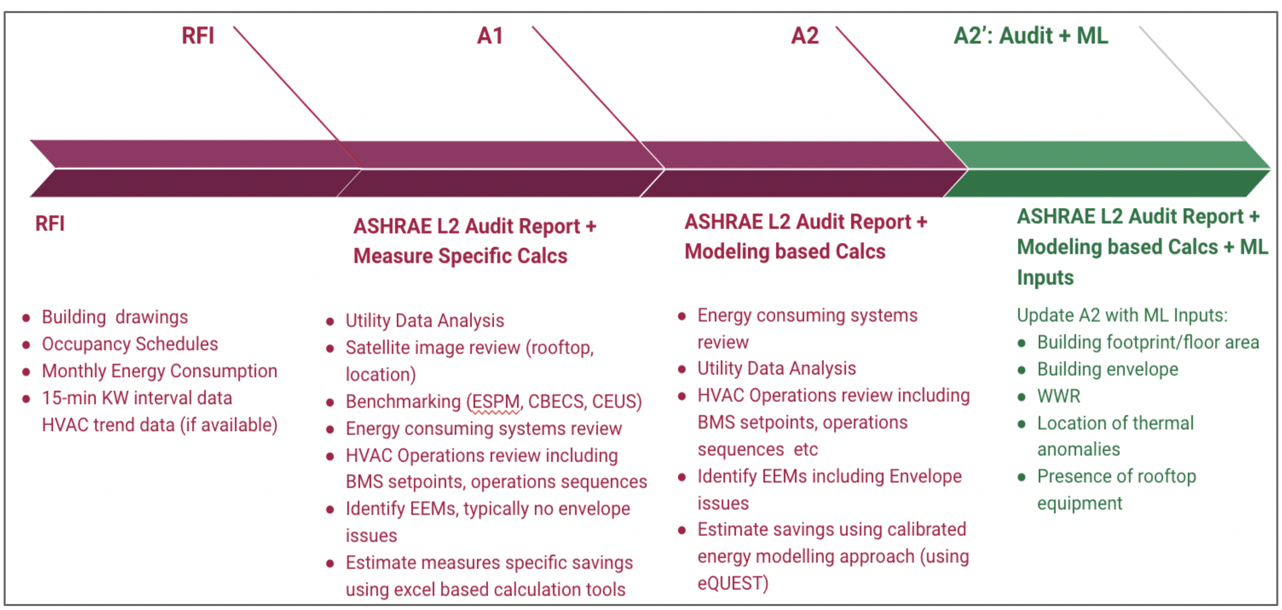

Figure 8: Typical audit workflow (pink) and integration with ML-derived outputs (green)

Table 2: Audit outputs generated for the project

A1 ASHRAE L2 Audit + Excel based calculation tools	**A1'** A1 augmented with ML info (geometry, possible zones of infiltration/ exfiltration and WWR) (not generated)	**A2** ASHRAE L2 audit + eQuest simulation model calibrated to annual energy use	**A2'** A2 augmented with ML info (geometry, possible zones of infiltration/ exfiltration and WWR)

Results of Step 4, Integrate and compare with remote assessments data analysis

Using the data collected from the site, four outputs were generated from this step as mentioned below (Note: The outputs of the remote assessment have not been included as that was not a contribution of this work). First, an R1 output was generated by conducting building envelope specific data assessments to develop a baseline building model in the Asset Score software tool. This included a smart meter-based utility data remote assessment to update the building occupancy schedule in the baseline building model and utilizing Asset Score software tool for assessing the energy efficiency. An R1'output was generated by augmenting R1 with reviewing the ML-derived information. Next, an R2 output was generated using eQUEST with the information collected and analyzed during the R1 remote assessment. This included parametric runs based on utility data review and BMS trend data review, anda savings summary based on proposed recommendations. An R2'output was generated by augmenting the eQUEST model with the ML-derived information. The savings summary was revised. The ML- augmented remote assessment workflow (Figure 9) and savings summary were assessed to determine what, if any, marginal benefits were obtained. The outputs are shown in Table 3.

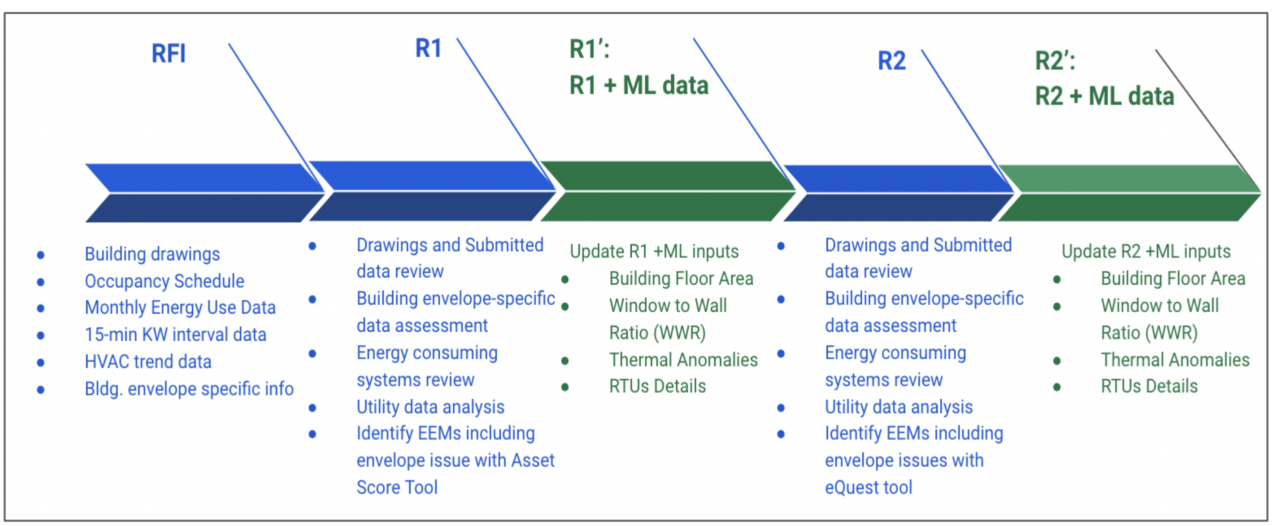

Figure 9: Typical remote assessment workflow (blue) and integration with ML-derived outputs (green)

Table 3: Remote assessment outputs generated for the project

R1 Envelope- specific data assessment + Smart meter-based remote assessment *Tools:* ECAM, Google Map, Asset Score)	**R1'** R1, augmented with ML info geometry, possible zones of infiltration/exfiltration and WWR) *Tools:* ECAM, Asset Score	**R2** Smart meter-based remote assessment + BMS data assessment + eQuest *Tools:* BMS inbuilt analytics, MS Excel, Universal Translator-3, eQUEST Simulation	**R2'** R2, augmented with ML info geometry, possible zones of infiltration/ exfiltration and WWR) *Tools:* BMS' analytics, MS Excel, Universal Translator-3, eQUEST

Results of Step 5, Synthesize the results to determine the value of new information

The results from Steps 3 and 4 were compared. First, the labor time to provide the ML-derived asset information (Table 4) and to conduct the audit, the remote assessments and provide the respective reports (Table 5) was tracked. Second, additional ML-derived information and its contribution to the audit/remote assessment reports was analyzed (Table 6). Third, the replicability of the methodology was assessed.

Tracking labor time and associated cost

The machine learning process included field work for UAV flight-based data capture, and desk work to utilize the ML algorithms and generate a report with the outputs in the desired file formats. The total time was ~10-12 hours each for the two test sites, as shown in Table 4. It is expected that the time taken can be reduced through report automation. Additionally, since a 3D point cloud generated for a building does not need to be repeated unless there are transformations, that would reduce the total time for any future analysis activities.

Table 4: Labor time for ML workflow

Labor Time	**Approach**			
	Planning, permit, flight	**Data processing**	**Report**	**Total**
Person-hours/medium sized building	5-6 hours (2 people, Pilot, Observer)	3-4 hours* Labor time for A3dbr and AutoBFE pipelines	2 hours	10-12 hours
Labor Cost[3]				
Total Cost/bldg	$560-$675	$375-$500	$250	~$1185-$1425

[3] Hourly rates: US $125 based on national average for an engineer, and US $100 for an observer.

*Does not include 5-10 hours of Pix4D 3D reconstruction processing time, that does not need manual supervision.

The labor time and associated cost for the audits and remote assessments, without and with the input of ML-derived information, is shown in Table 5 below. For the two test sites, the effort incrementally increased for first-time integration of ML-derived information with audits (4%), and incrementally reduced for first-time integration of ML-derived information with remote assessments (9-20%).

Table 5: Labor time for audit and remote assessments workflow

Labor Time	**Approach**			
	Audit	**Audit + ML**	**Remote**	**Remote + ML**
Person-hours/bldg*	A1 - 40 hrs A2 - 48 hrs	A1' - N/A A2' - 50 hrs (4% increase)	R1 - 20 hrs R2 - 44 hrs	R1' - 16 hrs (20% reduction) R2' - 36 hrs (9% reduction)
Labor Cost				
Total Cost/bldg**	A1 - $5,800 A2 - $6,720	A1' - N/A A2' - $7,000	R1 - $2,500 R2 - $6,380	R1' - $2,000 R2' - $5,220

* Assuming a medium sized building (50,000-70,000 sq.ft)
**Rate for A1 is US $145/hr, A2 and A2' are US $140/hr
**Rate for R1 & R1' is US $125/hr, R2 &R2' is US $145/hr (based on engineer rates in California)

We present an analysis of Table 5 and includes projections for cost and benefit of the ML method. A1 was a traditional audit (using excel spreadsheets) that typically does not include envelope measures. Hence, there was no A1' output. It is projected that if the ML-derived high-resolution data on envelopes and RTU be provided ahead of the audit (e.g., a "preliminary audit" before the site visit) that could provide high marginal benefit by helping guide the site visit to identify or prioritize data collection and save time and effort. The labor hour estimates for A2' show a 4% increase, and this included the additional time taken to assess and integrate the outputs from the ML data into the workflow for the first time. This is expected to reduce as the process is now understood and the workflow streamlined. It is also projected that potential features of ML data such as provision of the building footprint in CAD dwg format will reduce the time in creating the model.

The labor hour estimates for R1' show a 20% reduction and that for R2' show a 9% reduction, despite included the additional time taken to assess and integrate the information received from the ML-output report into the workflow for the first time. It is projected that ML-derived outputs can potentially reduce labor hours for remote assessments by 50%. It is projected that if significant envelope-related measures are identified from ML extracted data (e.g., leakages, lack of insulation etc.), additional time may be required to assess the measure for quantification, and for generating these comprehensive reports.

Tracking usability and marginal benefit

ML-derived information provided marginal benefits to the remote assessments and audits with inputs to asset information i.e., building 3D geometry, footprint, floor area, floor heights, number of floors, building height, WWR, presence of RTUs. Further, unprecedented EEM recommendations were enabled using the ML-derived thermal anomaly report. In this study, it was found that the WWR and potential thermal anomalies were the most valuable addition to the conventional audit and remote assessment. It was learned that a lack of diagnosis of the type of anomaly and associated metrics required the engineers to estimate the infiltration/ exfiltration of certain zones to incorporate these findings into the audit and assessment tools. Next steps also involve producing outputs that can be more readily integrated with existing audit and assessment tools and gaining more ground truth information on buildings such that more detailed performance metrics may be estimated. (See Conclusion section).

From Table 5, ML-derived outputs were able to reduce the effort required for the remote assessment and projected for the in-person audit as well, if they were provided before the audit was conducted. The marginal benefits of this ML-derived information were deemed 'high' if no "as-built" drawings were available for a site. The value of this information was deemed 'medium' if it was used to verify the "as-built" condition at site, even if design and construction drawings were available. The information could be even more valuable if (i) the accuracy was verifiable, and (ii) if the data were available during the preliminary audit to guide the site visit to identify potential envelope EEMs.

Discussion

Novel data used in ML techniques is typically hard to obtain from a site, due to issues like UAV flight permissions. Engineers performing the audit/remote assessment use default assumptions to complete their analysis such as ASHRAE 90.1 or California's Title 24 defaults in eQUEST. However, since the ML output report provided more information about input parameters, the assessor used these new data to input validated information rather than using default eQuest values. ML methods improved both in-person and remote assessment processes through complementarity and verification.

There is a high potential to accurately and cost effectively acquire unstructured data sources at scale. Once scale is achieved, the method can also become helpful to quickly identify what types of building facades (e.g., punched windows vs. curtain walls etc.) may be associated with certain thermal anomalies. At that point it will be possible to perform a direct comparison of measures recommended, measures installed, and eventually energy savings achieved by buildings that implement these new techniques - as well as the cost and time required to achieve these outcomes - relative to both existing remote assessment methods and in-person audits.

The practical requirements to replicate the process include obtaining the requisite permissions to fly the UAVs and acquire data on the site, access to a pilot for a UAV equipped with an RGB and thermal cameras, and short trainings on image data acquisition and post-processing using LBNL's open-source algorithms to extract the relevant information. While the cost could be ~USD 1000 for a medium sized building, this process be streamlined to be made more cost effective using better camera types, pre-developing optimal flight path designs, optimizing temperature step functions to reduce data acquisition costs, and optimizing training and analysis.

The core benefits of this method are that it is a non-contact, non-destructive, and replicable, and can be utilized for verifying and/or augmenting information for current building energy analytics tools. Once adequate technology readiness levels have been achieved, the machine learning method can be highly replicable by identifying relevant business models for target market segments.

Conclusions

In this research, new ML-derived information extraction techniques were developed and tested for their potential to provide accurate new or complementary information streams for existing building energy analytics tools i.e., Level 2 audits and remote assessments. They were assessed for their likelihood to provide meaningful asset information and improved efficiency insights beyond the current state-of- the-practice, and the potential for at-scale cost effectiveness. Five parameters were extracted using new machine learning algorithms: (i) building footprint and floor area; (ii) 3-D building envelope including the total building height, number of floors and floor height; (iii) window-to-wall ratio; (iv) envelope thermal anomalies, and (v) the presence and number of rooftop energy equipment such as rooftop HVAC units.

There are two key marginal benefits gained from ML-derived information. First, in augmenting information otherwise accessed through drawings and satellite images: This is through information about the “as-built”, i.e., current conditions at the sites that could help provide new information if there were no current site drawings/information available, as well as provide ground-truth to any available design drawings. At both test sites, ML-derived data helped to augment the design drawings when developing building simulation models during the audit process and for spreadsheet models during the remote assessments. ML-derived information was also better than just having regular site photographs– it helped inform/verify three parameters: the building footprint and floor area, heights, and number of floors. In addition, while information about window-to-wall ratio and rooftop units is currently extracted from google street view and satellite images, the new ML-derived information about the RTU units is much higher resolution and therefore more useful. The ML-derived information was verified through the existing drawings as exhibiting a high-level accuracy (+/-10%).

The second key benefit is in providing unprecedented information not available otherwise: This was through providing new information about thermal anomalies that could not otherwise be obtained. These data could be directly overlaid on the audit and remote assessment analyses and provide/ improve the envelope measure recommendations. This was the most significant gap addressed by the machine learning methods. As next steps, the engineers expressed an interest to obtain the type, precision of location, and magnitude of the thermal anomaly. Quantitative information (such as % affected area and insulation R-value etc.) could help them provide more specific, prioritized envelope retrofit recommendations. This could provide greater payback opportunities especially in non-mild climate zones.

There are a few areas for potential future work, addressing technical and implementation aspects. First by enhancing envelope thermal anomalies detection and diagnosis with greater accuracy and precision: This includes accuracy of the magnitude, precision of the location, accuracy of the data as compared to the auditor's visual inspection or blower door tests (for residential buildings). The core of this future work would be diagnosing the thermal categories such as air infiltration/exfiltration due to thermal bridges or breaks that lead to surface condensation enabling mold growth, deterioration of the building fabric caused by interstitial condensation, and occupant discomfort caused by draughts and cold rooms. Thermal bridges can typically occur at the junctions between the wall, floor, or roof, near windows and doors, by studs, and around holes for cables and pipes. Others include exterior surface temperature of the roof and glazing, and convection or conduction issues through wall insulation.

Second, by extracting detailed information on asset and energy equipment. While in the scope of this study, identification of an RTU's presence and general location was done, additional information about RTU and potentially solar equipment sizing (e.g. nameplate information extracted through closer UAV flights and optical character recognition and tonnage), and wear and tear could help with improved asset and EEM identification. Another aspect is to improve the model for the automating WWR extraction. Others include initiating an automated approach for extraction of the number of floors and materials. These aspects are relevant to identifying equipment efficiency, installation, and replacement that are a significant gap with remote assessments.

Third, by potential improvement in the integration of ML-derived outputs: This includes pipelines through which outputs from the ML pipeline could be integrated with existing tools and methods. For example, how fully automated WWR and 3D building reconstruction could be 'passed/input' to a simulation tool (Geojson and numeric values), or .dwg format of images 2D or 3D that could be 'passed' for consumption by an EMIS or simulation tool

Certain target segments, applications, and collaborations may be well-served by this new ML methodology. Since auditors' experience shows that envelope measures rarely pay in mild climates, they tend to spend their limited budget on measures that are likely to be more fruitful. However, in non-mild climate zones that exist across broad swathes of the U.S. (say ASHRAE climate zones 1-3, and 5-8), envelope retrofits may be beneficial. Additionally, as code compliance and healthy buildings are becoming increasingly important, regular maintenance to help eliminate sub-par energy and/or health/ comfort-related performance has also become necessary especially in older, multifamily buildings. Providing specific information from machine learning based envelope retrofits could help prioritize energy and comfort measures such as simple weatherization. The methodology presented in this paper can also be applicable to a neighborhood of single family residential and multifamily buildings, reducing the time and effort required for characterizing the assets of each one separately. At the same time, privacy becomes a bigger concern when it comes to residential buildings and future work must incorporate scalable permits and practices for drone flights and image capture that address this. Funding that is otherwise used for audits or remote assessments may be re-allocated to actual envelope measures such as better shading and glazing, insulation, cool roofs etc.

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