Machine Learning for Improved Efficiency Analysis and Asset Information

Brown Bag Webinar for DOE Building Technologies Office

5/19/20

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Partners

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Outline

- Overview
- R&D Outcomes
- Next Steps

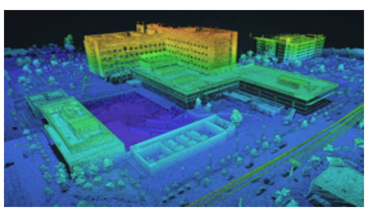
Opportunity

- Recent advances in public data availability (disclosures and permit data), sensor technology, and falling costs

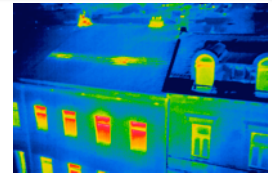
- Increasing number of data collectors for buildings

- These novel data + feature extraction hold promise to ID
  - Building characteristics and assets
  - Building-specific EE measures

Types of Data



RGB & THERMAL IMAGES



STREET VIEW

AERIAL / SATELLITE IMAGES

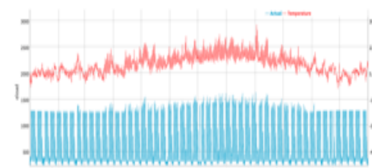
LIDAR

Features Extraction Tools:

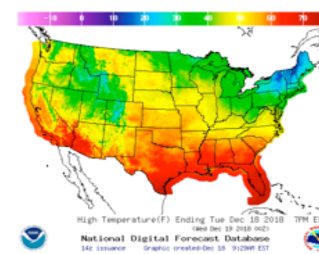
- Machine Learning
- Image processing
- Energy Analytics
- Natural Language Processing

PUBLIC DATA

METER DATA



WEATHER DATA



DATA FUSION

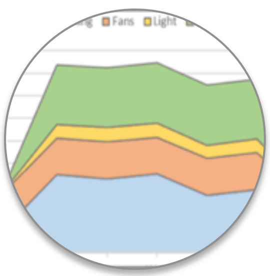
BUILDING CHARACTERISTICS

EFFICIENCY OPPORTUNITIES

Project Objectives

- Apply machine learning (ML) to unstructured data sources to improve inputs to, performance of state-of-the-art efficiency analytics tools
- Characterize performance relative to current state of practice
- Determine broader market potential and pathways to integrate with existing toolsets and workflows

Theory of Change



Meter

+

Imaging

street, aerial/satellite, LIDAR, thermal

Public

Unstructured data

=

Enhanced building characterization

Improved energy-efficiency measure identification

Cost-effectiveness, reduced labor time vs. conventional building audits, tools, and EMIS

LIDAR: Light Detection and Ranging

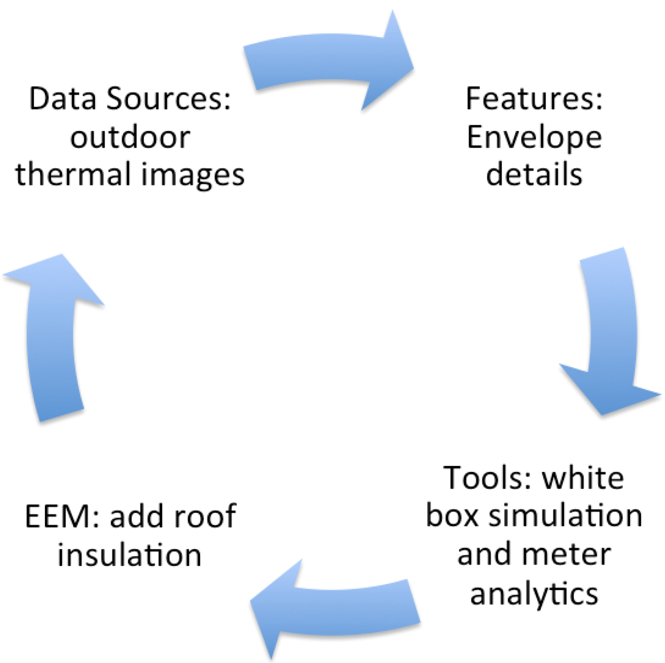
EMIS: Energy Management and Information Systems

R&D Achievements

- Opportunity analysis to apply machine-learning for enhanced efficiency; baseline state-of-the-art/practice
- Open solutions for satellite/aerial image footprint extraction
- Drone-based feature extraction, i.e. generation of 3D geometry and thermal profiles

Opportunity Analysis

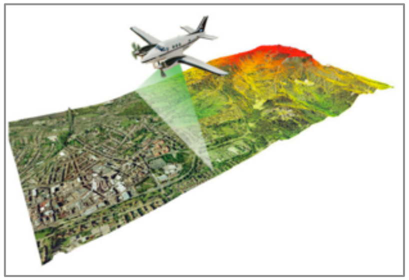
Overview of the Analysis



- Concrete assessment of how novel data sources can be used to enhance asset/measure identification
- Information regarding data availability, providers, and methods of collection

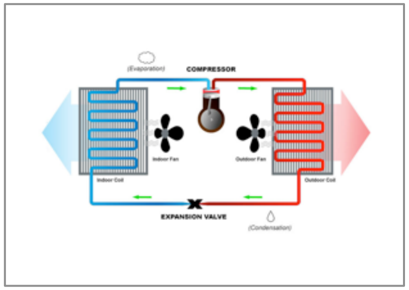
Scope of the Analysis

- 27 data sources
  - Public data, e.g. LIDAR, assessor, energy disclosures
  - Proprietary data, e.g. property real-estate
  - Researcher datasets, e.g. indoor/outdoor thermal images
  - Private, e.g. interval meter, EnergyStar Portfolio Manager, work orders



- 18 features
  - Energy e.g. actual energy use
  - Equipment e.g. equipment inventory
  - Weather, e.g. actual weather
  - Envelope e.g. building vintage, external geometry
  - Interior, e.g. interior geometry
  - HVAC, e.g. indoor temperature preferences
  - Context, e.g. building use, operation details, change records
  - Surroundings, e.g. shading
  - Occupancy, e.g. opening hours, estimated occupancy
  - Cost e.g. utility cost

- 69 energy efficiency measures: capital, controls, and maintenance
  - Lighting
  - Envelope
  - HVAC
  - Service hot water
  - Plug and process load
  - Renewables
  - Storage



Mapping EEMs to Data Sources

(Illustrative excerpt)

System	Energy Efficiency Measure	Type of EEM	Cost	Required data (from literature)	New Data Source to Improve Assessment	Notes
Lighting	**Calibrate exterior lighting photocells**	Control	Low	Audit	-	High impact on simulation results.
Lighting	**Install occupancy sensors to control interior/exterior lighting**	Capital	Medium	Lighting energy consumption estimation/Audit	*BaseOp* (Smart Thermostats [16] OR BAS Trend log [24], Wifi data [18], Commercial Business Opening Hours [4], Interval Meters [14], Interval Sub-Meters [26]); *SysCtrl* (BAS Trend log [24])	High impact on simulation results.
Lighting	**Re-circuit and schedule lighting system by zone**	Capital	Medium	Lighting energy consumption estimation/Audit	*BaseOp* (BAS Trend log [24], Interval Meters [14] OR Interval Sub-Meters [26])	
Envelope	**Reduce envelope leakage**	Maintenance	Medium	Audit	*SysInfo* (Outdoor Thermal Images [10] OR Indoor Thermal Images [11], Weather from Online Stations [15]) *BaseOp* (Interval Meters [14] OR BAS Trend log [24] OR Smart Thermostats [16])	Thermal image --> Leakage HVAC consumption (from smart meter data) + zone temp + outdoor air temperature --> poor envelope performance
Envelope	**Replace wornout weather stripping at exterior doors**	Maintenance	Low	Audit	*SysInfo* (Outdoor Thermal Images [10] OR Indoor Thermal Images [11])	Thermal image --> Leakage
Windows	**Replace windows and frames**	Capital	High	Audit	*SysInfo* (Outdoor Thermal Images [10] OR Indoor Thermal Images [11])	Thermal image --> Leakage Outdoor 3D image --> Size and location of Window
Windows	**Add overhangs (attachments) to windows**	Capital	High	Audit	*SysInfo* (Outdoor Thermal Images [10])	Thermal image --> Low R-value Outdoor 3D image --> Geometry
HVAC	**Clean cooling and heating coils and comb heat exchanger fins**	Maintenance	Low	Audit	-	-
HVAC	**Repair airside economizer**	Maintenance	Low	RTU MAT, OAT, RAT, compressor status, fan	*BaseOp* (Weather from Online Stations [15], BAS Trend log [24 OR, Smart Thermostats	
Service hot water	**Upgrade to heat pump water heater**	Capital	High	Audit	*SysInfo* (EnergyStar Portfolio Manager [22])	Breakdown a building's heating and cooling performance with ASHRAE IMT
Plug and process load	**Purchase energy efficent office and sales equipment**	Capital	Medium	Audit	*BaseOp* (Interval Meters [14] OR Interval Sub-Meters [26])	Plug load inferred as: total meter - (inferred or submetered) HVAC - inferred
Renewable	**Install solar PV**	Capital	High	Audit	*SysInfo* (Satellite, Aerial imagery [6]) *BaseOp* (Weather from Online Stations [15])	Weather data + GIS + aerila image to identify opportunities for solar installation
Storage	**Thermal and electric storage**	Capital	High		-	

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Mapping Data Sources to Features

(Illustrative excerpt)

ID	Data Source Description	Type	Existing vs Research	Data Ownership	Building Type	Information Derived from Data (Features)	Feature Short Name	Provider	Collection Strategy	Challenges in Gathering/Processing Data
1	**Property Real-Estate information**	Text	Existing	Proprietary	(Res), Com	building size, vintage, major renovations, # tenants, type of businesses	FloorArea, Vintage, BuildMod, BuildUse	Real-Estate db companies (e.g., CoStar, Zillow, etc.)	Connect to API	Not open-source
2	**Assessor Data**	Text	Existing	Public	Res	building size, vintage, bedrooms and baths count, etc.,	FloorArea, Vintage, IntGeometry, BuildUse	Counties (eg. LA county)	Scrape from Web or Connect to API	Fragmented, Not available online for all counties
3	**City Building Permits**	Text	Existing	Public	Res	building upgrades and triggered code compliance (HVAC, insulation, ...)	BuildMod	City records (eg SF)	Scrape from Web	Fragmented, Not available online for all cities, Permits may not be representative of actual upgrades in buildings
6	**Satellite, Aerial imagery**	Images	Existing	Public, Proprietary	Res, Com	building geometry, count of visible hvac units, roof info	ExtGeometry, EquipInventory	Google Maps/Earth, OpenAerialMap, NearMap	Connect to API	May need ML to process raw images. Some areas (rural) do not have granular maps. Maps may not be up to date.
7	**Building footprint data**	Text (e.g., GIS)	Existing	Public	Res, Com	building footprint, height, number of stories	FloorArea, ExtGeometry	Cities (eg. SF, Chicago, LA, Atlanta), Microsoft, Open Street Map (OSM)	Download from Website, API	Data quality. Building height information can be missing.
8	**Digital Surface Model (DSM) == Aerial Lidar Data**	Text (e.g, laz files)	Existing	Public	Res, Com	Building Height, vegetation	ExtGeometry, Shading	USGS	Download from Website, API	Only some areas are covered and the data maybe old
9	**Outdoor 3D Images**	Images	Existing	Public	Res, Com	building geometry, window/wall ratio, roof info	ExtGeometry	Google Maps/Earth	Connect to API	May need ML to process raw images. Some areas (rural) do not have granular maps. Maps may not be up to date.
10	**Outdoor Thermal Images**	Images	Research	Research datasets owned by researchers	Res, Com	Exterior surface heat signature, i.e. difference in radiation. Heat loss from the envelope. Exposed ducts heat loss.	EnvelopeDtls	-	Drone, Car + camera	No open datesets
11	**Indoor Thermal Images**	Images	Research	Research datasets owned by researchers	Res, Com	Heat Loss by air leaks and lack of insulation	EnvelopeDtls	-	Person + Camera	No open datesets
12	**Lidar Data**	Images	Research-Existing	One Public dataset	Res, Com	building geometry, window/wall ratio, detailed information about the	ExtGeometry	Researchers Website	Drone, Car + Lidar sensor	Small dataset for NY.

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Mapping Features to Tools

(Illustrative excerpt)

Feature Short Name	Feature (Type of Information)	Feature Category	Simulation: Improved Use	Data-Driven: Improved use	White-Box Simulation Tool (CBES, AST, HES)	Data-Driven Virtual Audit Tool
ActEnergyUs	**Actual Energy Use**	energy	Information (equipment type, envelope characteristics, operation schedules) extracted from the time-series data can be used to refine the modeling assumptions	Used to evaluate the potential savings given the sub-system energy use, the baseline system operation and the suggested EEM. Typically necessary in all data-driven tools.	Used to calibrate model	Used to train model
EquipInventc	**Devices/Equipment inventory**	equipment	Used to refine assumptions related to equipment (type, efficiency level)	Used to refine assumptions related to equipment installed, exclude EEM (eg. skylights already present) and to quantify cost in the cost benefit analysis (i.e., cost can be related to the number of units to be replaced)	Used to create and or calibrate model	Used to train model
ActEquipUse	**Acutal Equipment/Appliance Use (or runtime)**	equipment	Used to refine assumptions/inputs related to equipment (run time, characteristics)	Defines the baseline operation of the equipment or system. It can be used to evaluate savings for a different control scheme control-based measure. It can be used to estimate an energy baseline (e.g., thermostat runtime)	Used to calibrate model	Used to train model
InferEquipUs	**Inferred Appliance Energy Use or Schedule**	equipment	Used to refine the peak power, power density, and operation schedules of specific equipment/appliances	Similar to the feature above but estimated instead of measured.	Used to create and or calibrate model	Used to train model or help disaggregation
OperatDtl	**Building operation details**	context	Used to refine assumptions related to building operation hours	Work orders and Maintenance Log can be used to identify EEMs related to poor performance of equipment, known occupant complains etc. They can also be used to reduce priority of operational measures on equipment recently maintained.	Used to identify savings opportunities	Used to identify savings opportunities
TempPrefer	**Indoor temperature preferences**	HVAC	Used to refine indoor temperature setpoint schedule assumptions	Temperature preferences can help recommend adjustment in control strategies.	Used to create model (define HVAC schedule and setpoints)	Used for more precise disaggregation (HVAC load)
ActWeather	**Actual Weather**	weather	Used as actual weather data input to the simulations.	Used to normalize energy consumption when comparing with operation in other periods. Also used together with thermal images to determine envelope characteristics.	Used to calibrate model and project energy use to other conditions	Used to train model or help disaggregation
FloorArea	**Building floor area**	envelope	Used to calibrate auto-generated building models	Used to normalize energy savings for benchmarking with other buildings.	Used to create model (size of zones)	Used to evaluate EUI
Vintage	**Building vintage**	envelope	Used to refine the building vintage assumptions	Used to infer most likely type of envelope and equipment.	Used to create model (define envelope, equipment and performance curves based on averages)	Used to select components of model (based on assumptions)
ExtGeometry	**Building External Geometry**	envelope	Used to refine inputs related to envelope	Used to identify building, # floors, shading that may prioritize certain EEMs.	Used to create model (define size, windows size, ...)	Used to select types of model (based on assumptions)
EnvelopeDtl	**Building envelope characteristics**	envelope	Used to refine inputs related to envelope	Used to assess the need for envelope measure, such as adding insulation, reduce leakage, etc	Used to create model (define structure characteristics)	Used to select types of model or constrain model coefficients
Shading	**Shading**	surrounding	Used to refine geometry modeling of building block simulations	Used to evaluate the potential of using shading as EEM.	Used to refine model (shading)	-
IntGeometry	**Building Internal Geometry**	interior	Only used in highly detailed customized models, not so much in generalized tool case	Used to visualize internal elements related	Used to create model (zoning, internal mass)	Used to select types of model or constrain model coefficients
EstOccupanc	**Estimated Building Occupancy**	occupancy	Used to refine inputs related to operating hours or number of occupants, and schedules	Used to assess opportunities for changes in equipment schedules.	Used to create model (define occupancy heat loads) and opportunity for savings	Used to identify savings opportunities
OpHrs	**Building/Business Opening Hours**	occupancy	Used to refine inputs related to operating hours or number of occupants, and schedules	Used in analysis to identify EEMs that impact scheduling of equipment and operation.	Used to create model (define occupancy heat loads) and/or equipment schedule	Used for more precise disaggregation and identify savings opportunities
BuildUse	**Building use**	context	Used to select reference model	Used to exclude EEMs related to non-pertinent systems (e.g. process load in an office) or to have a better estimate of sub-system load.	Used to create model (define type of equipments, schedules, energy uses)	Used for more precise disaggregation
BuildMod	**Building change records**	context	Used to define equipment characteristics	Used to identify whether systems have recently been updated or replaced. May exclude some EEMs.	Used to improve envelope or equipment assumptions	Used to improve envelope or equipment assumptions
EnergyCost	**Utility Rates**	cost	Used in cost effectiveness assessments	Used in the cost-benefit analysis	Used to identify savings opportunities	Used to identify savings opportunities

Key:

CBES: Commercial Building Energy Saver

AST Building Energy Asset Score Tool

HES: Home Energy Saver

EIS: Energy Information System

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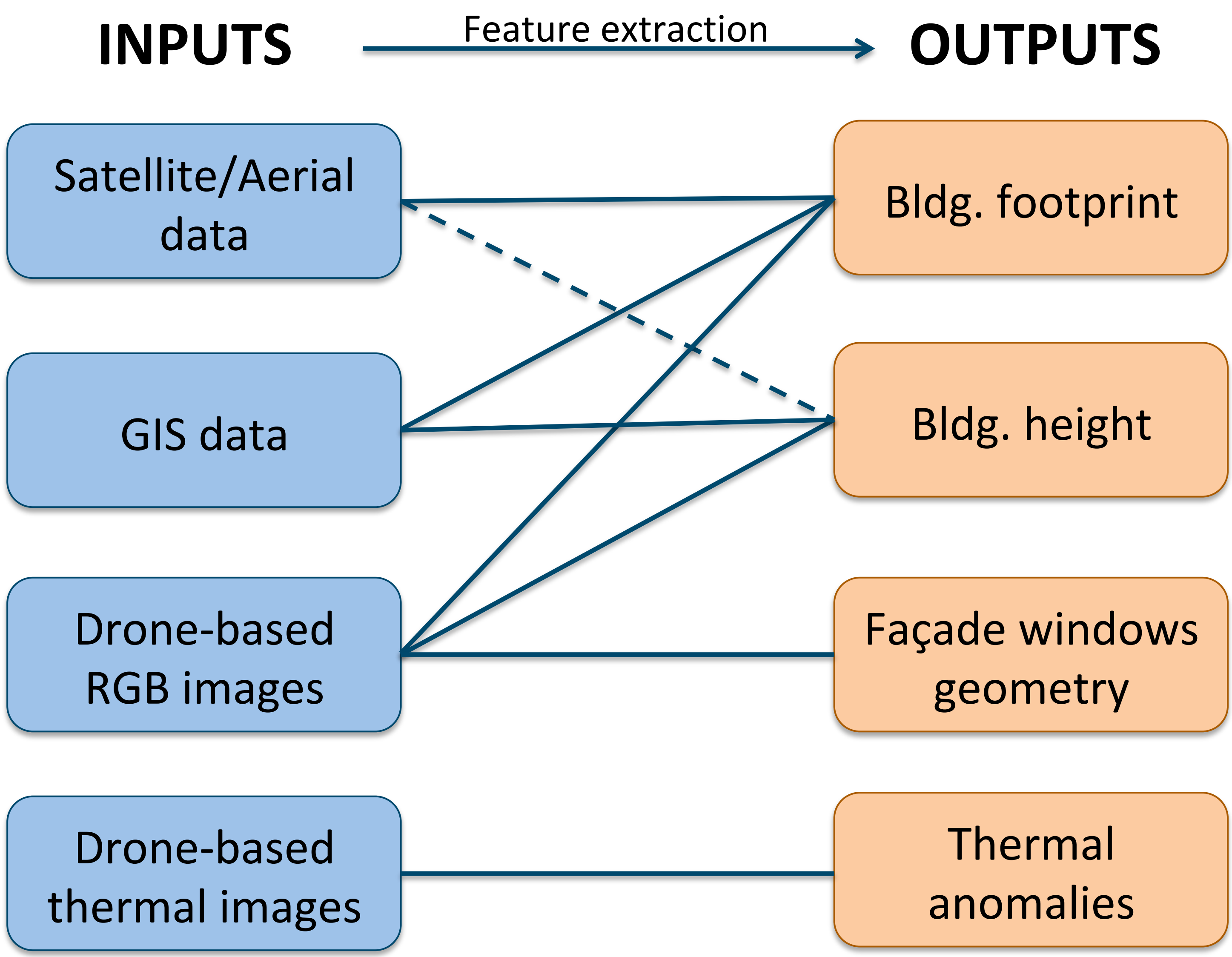
Three Most Promising Data Sources

Of the 27 data sources considered, those identified for immediate focus were:

- Satellite/Aerial data
  - High availability and potential to scale
  - Several sources
- Buildings footprint GIS data
  - Openly available for many U.S. cities
  - Relatively easy to extract and process
  - Combined with satellite/ aerial images and machine learning, can build accurate models to extract building footprint where GIS footprint data unavailable
- Drone-based visible and thermal images
  - High resolution (10X satellite images) can be captured
  - High potential to assess buildings envelope characteristics
  - Can facilitate inspection of hard-to-reach areas, without compromising safety

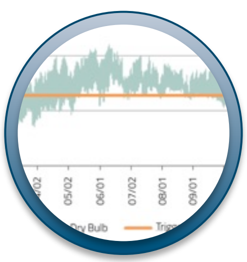
Data Inputs and Outputs



Baseline State-of-the-Art/Practice

Baselining Approach

Traditional building audits



Advanced analytics tools

- Review prior studies of efficacy of meter-based remote assessment tools, and data from auditing programs
  - Literature
  - Data from LBNL R&D
  - Data from TRC audit projects
- Quantify typical measures identified, associated labor time/cost
- Use findings as baseline to assess newly developed analytics approaches

Time and Cost, Remote Assessments and Audits

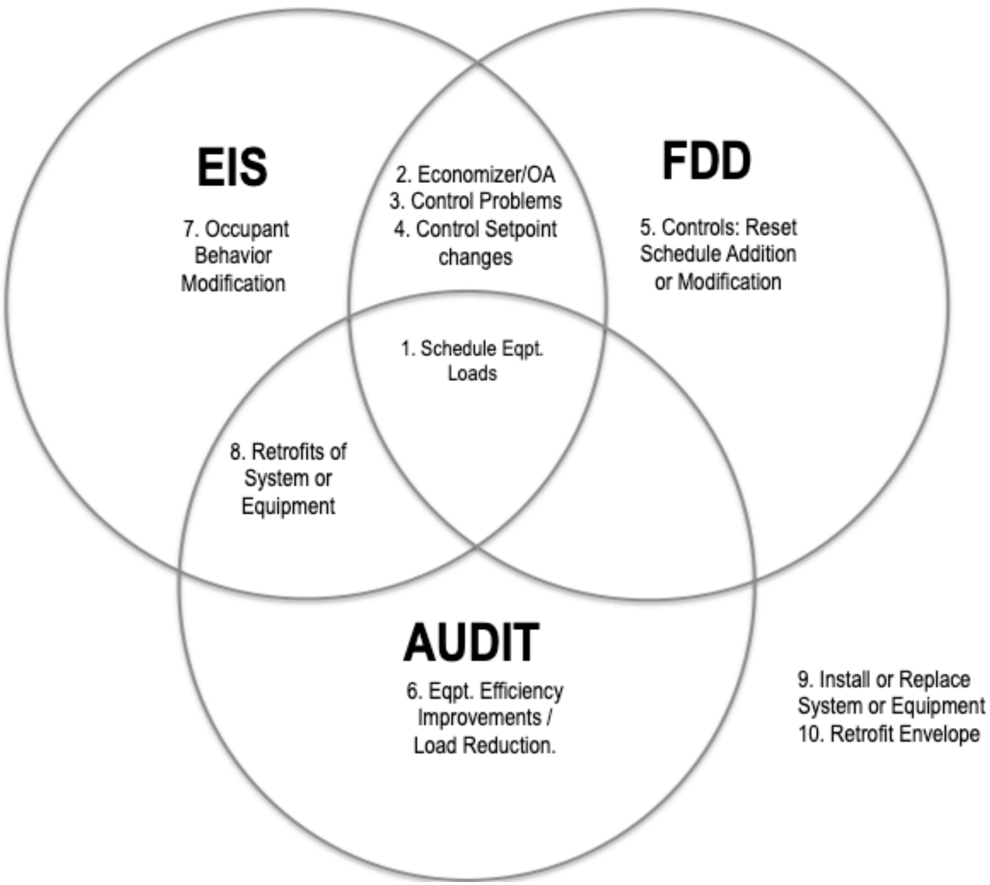
Time

- Audits: One-time event, conducted by service provider
  - Large building (>100K sf) level 3 median time 480 person-hours
- Remote assessments: ongoing, by providers and building staff
  - Configuration time 27-160 person-hours in first year
  - Ongoing usage time 240-420 person-hours per year per building

Cost

- Level 3 large building audits median cost $0.17/sf, $13.6K/bldg.
- Remote assessments
  - Upfront: $.01-$.06/sf, $1.1-$11K/building
  - Ongoing: $.03-$.07/sf

EEMs Typically Identified in Remote Assessments and Traditional Audits



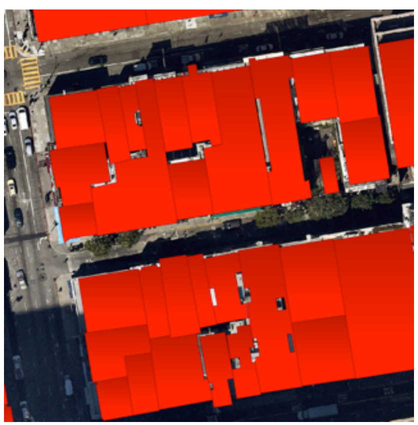
- Areas of opportunity to enhance remote assessment technology
  - Envelope retrofits
  - Equipment efficiency, installation, and replacement
- Not well covered in audit or today's analytics tools

EIS: Energy Information Systems
FDD: Fault Detection Systems

Replicable, Open Solutions for Satellite/Aerial Image Feature Extraction

Prior and Current Work

- Prior research in semantic segmentation and computer vision for building footprints
  – Microsoft US dataset, based on convolutional neural networks (CNN); limited description of the model, training dataset not provided
  – Other benchmark datasets limited to a small number of cities, not generalizable



- Current project
  – Open workflow, training data and state-of-the-art deep learning image segmentation algorithms

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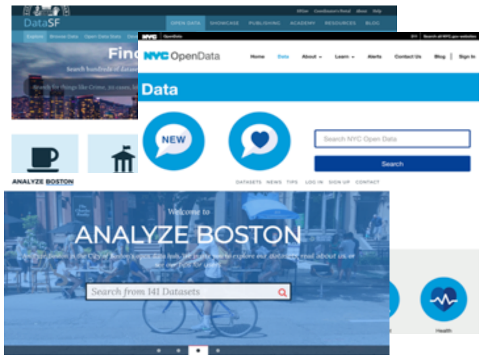
Replicable Workflow with Three Modules

Open-source Automated Building Footprint Extractor (AutoBFE) on Github: https://github.com/LBNL-ETA/AutoBFE

- Data preparation module: Generate training data using limited manual effort with openly available data sources
- Deep learning modeling module: Easy modeling pipeline to reproduce analysis and test new deep learning architectures
- Post-processing of model results module: data formats compatible with required inputs to existing measure-identification tools

Data preparation module



GIS open data

Open Data GeoJSON files

Buildings Footprint

Generate training data using limited manual effort

- Automatic generation of training features masks by querying footprint GIS open data
- Automatic extraction of satellite/ aerial tiles using Mapbox api

Data preparation module

tiles_cover: Generate slippy map tiles coordinates covering the GeoJSON

mapbox_download: Download satellite/ aerial images using Mapbox API

map_masks: Generate masks tiles from the GeoJSON file

split_data: Split the masks and the images into training, validation and test datasets

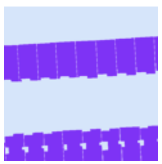
Deep learning semantic segmentation module

Training Dataset

masks

images

Validation Dataset



masks

images

DL semantic segmentation module

(Deeplab V3+)

Training

Standardized easy modeling pipeline to reproduce analysis and test new deep learning architectures

(Scalable: Training can be done on a Multi-GPU hardware)

Best Model selected using the accuracy computed on the validation dataset

Test/prediction Dataset

images

Prediction

Probabilities maps (i.e., probability of each pixel being a building or not)

Post-processing of model predictions module

Predicted Probabilities maps

Results easily transformable into GeoJSON data format

- Predictions cleaning using computer vision algorithms (i.e., morphological transformations)
- Convert predictions that are pixel-based masks into polygons with geographic coordinates (i.e., GeoJSON)

Post-processing module

get_masks_from_probs: Convert probabilities maps into masks a

get_polygon:

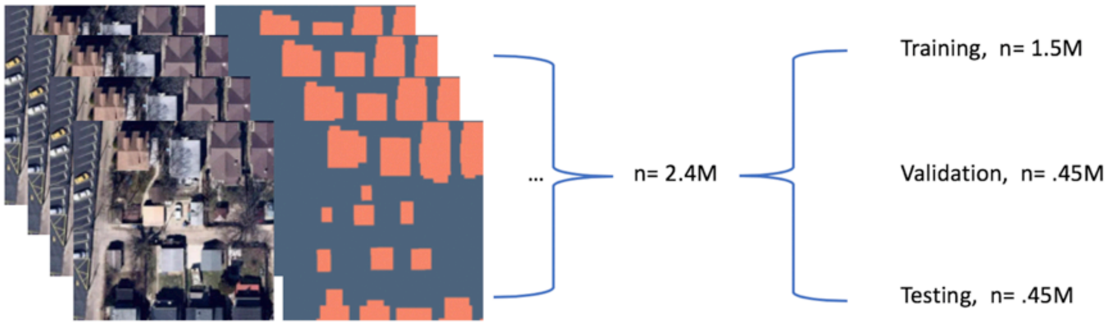
1) Apply morphological transformation on the generated masks to clean them from noise

2) From each resulting mask extract polygons of each detected buildings

merge_polygons: Merge all the polygons into one unique GeoJSON file that covers the prediction region (e.g., city)

Case study using AutoBFE

- Collected GIS data and Satellite images from 14 cities and 6 counties:



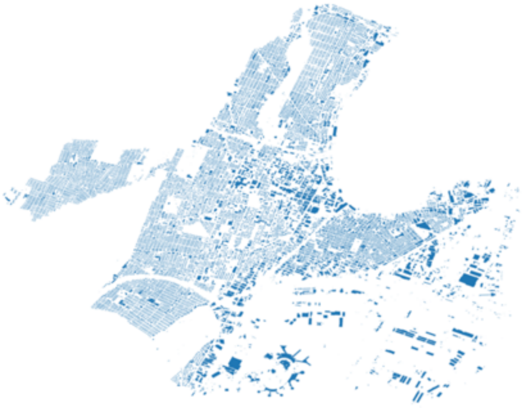
- Generation of prediction GIS files:
  – The model trained (on ~ 1.5 Millions images) has been used to generate prediction masks of the considered cities using satellite images extracted from Mapbox using AutoBFE tool
  – The prediction masks were post-processed to generate a GIS file (i.e. GeoJSON file)

- Quantitative/ qualitative comparison with state of the art openly available footprint data source (i.e., Microsoft footprints) :
  – Accuracy of the predicted footprints is performed using F1 score
  – Number of detected buildings
  – Visual comparison of the foot prints
  – Comparison of generated UBID for some selected examples

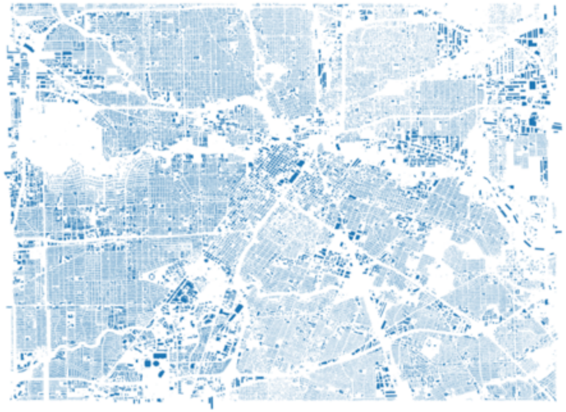
Comparison between Microsoft footprints and predicted footprints using AutoBFE

- Data from 3 "cities" has been used (i.e., NY, Newark and Houston):

Area from NY



Newark



Area from Houston

  - Newark and Houston not used during training of our model
  - 60% of NY data has been used in training process
  - No available information whether any on these cities have been used for training Microsoft model
  - Actual data available from the cities' open data web portals

Comparison Methodology: Prediction Accuracy

Prediction Accuracy

DeepLab V3+ Model (our model)

	NY	Newark	Houston
F1 Score	95.1%	94.3%	95.3%

Microsoft Data

	NY	Newark	Houston
F1 Score	92.4%	93.4%	94.4%

Number of Independent Footprints

Cities' open data

	NY	Newark	Houston
# of footprints	120,886	44,853	198,671

DeepLab V3+ Model (our model)

	NY	Newark	Houston
# of footprints	47,788	41,409	185,814

Microsoft Data

	NY	Newark	Houston
# of footprints	20,939	24,930	144,072

F1 score is a measure of the accuracy in binary classification (in our case the pixel is part of a building footprint or not), " It considers both the precision p and the recall r of the test to compute the score: p is the number of correct positive results divided by the number of all positive results returned by the classifier, and r is the number of correct positive results divided by the number of all relevant samples (all samples that should have been identified as positive)" (wikipedia). F1 score equal to 100% is the best value!

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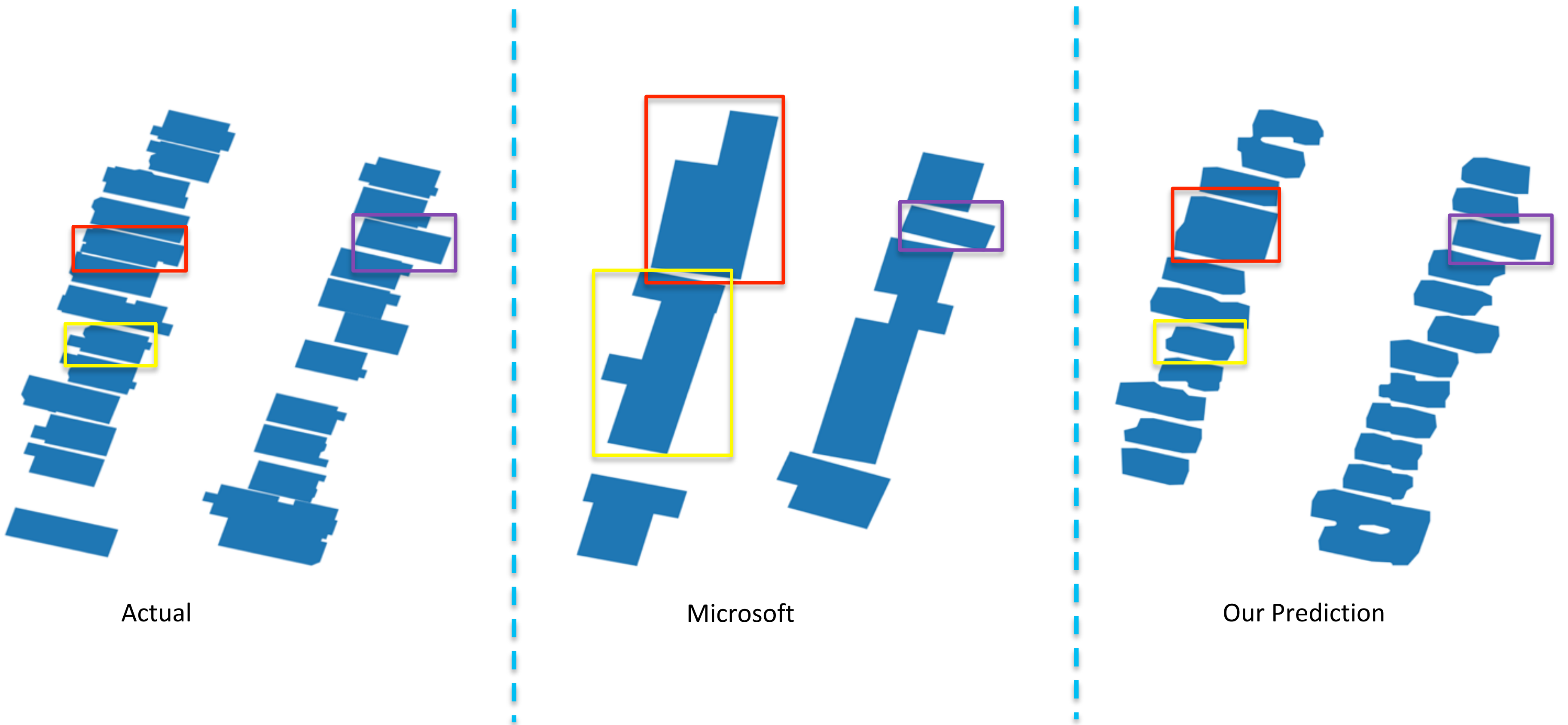
Visual Comparison

An example from Newark

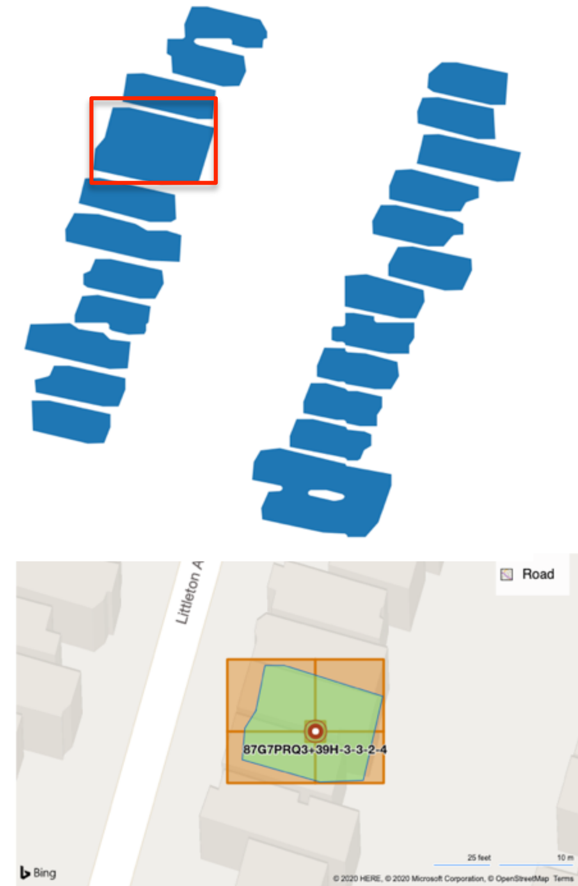


UBID Comparison

Example 1

Actual

Microsoft



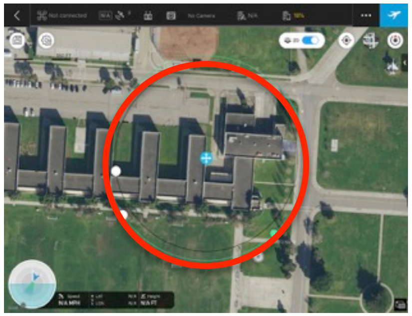
Our Prediction

Drone-based Generation of 3D Geometry and Thermal Anomalies Detection

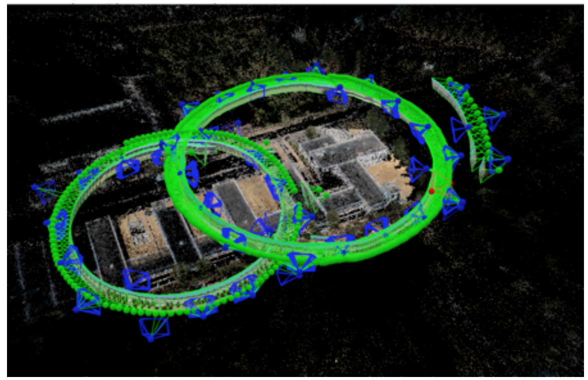
Drone-based Buildings Feature Extraction: Steps Undertaken

- Designed the drone system
- Defined the data acquisition methodology
- Developed a workflow to **automatically** extract the 3D geometry
  - Automatic buildings foot print extraction
  - Automatic height estimation
  - Automatic 3D model generation under a GIS format (e.g., GeoJSON), readable by existing EE tools
- Initiated development of a workflow to estimate windows to wall ratio
- Established foundation for drone thermal images capture and processing
- Developed preliminary computer vision approach to detect thermal anomalies

Drone-based Generation of 3D Geometry: Workflow

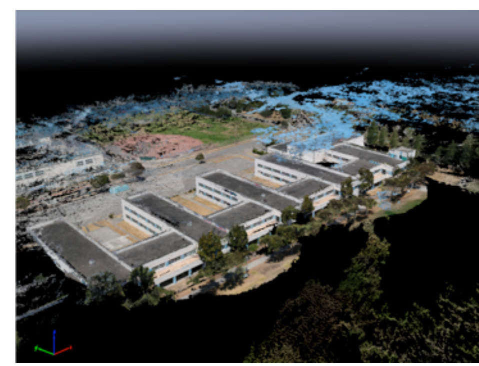


Planned flights

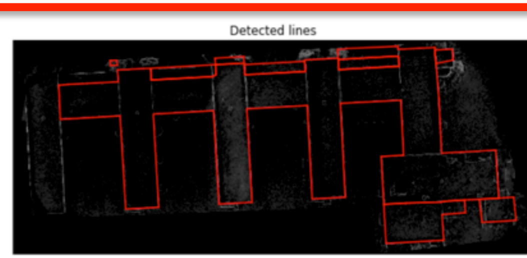


Position of the drone during the data capture

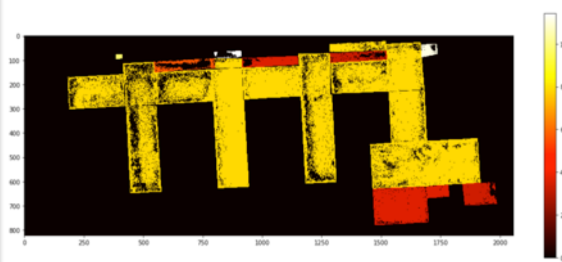
Collected imagery (2D)



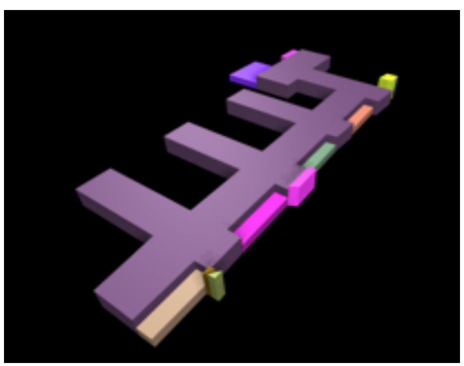
3D Reconstruction (Photogrammetry)



Estimated building footprint

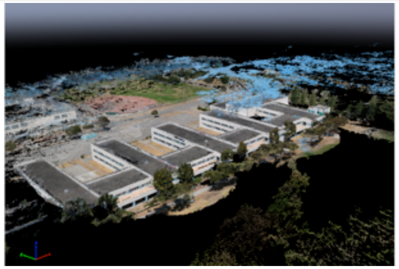


Estimated building heights



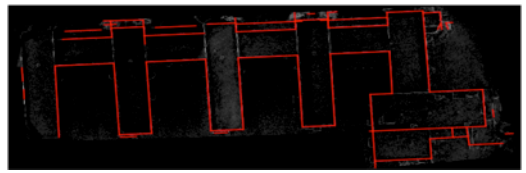
Building 3-D model (GeoJSON format)

Drone-based Generation of 3D Geometry: Process Details

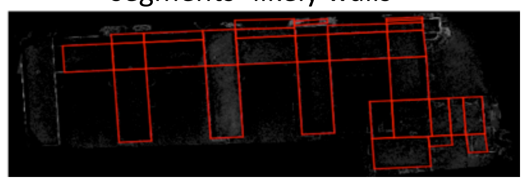


3D Point clouds
Photogrammetry

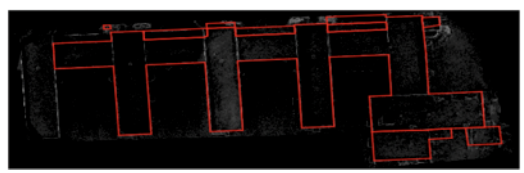
2D projection of the 3D point cloud



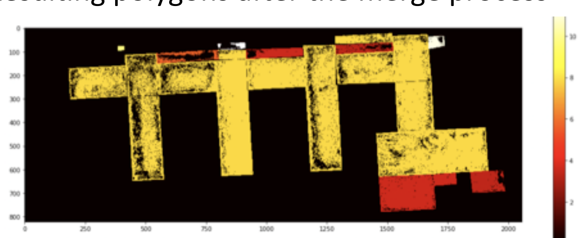
Apply Hough transform to extract line segments- likely walls



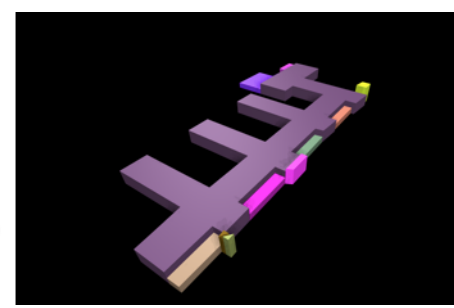
Polygonization



Resulting polygons after the merge process



Estimated heights of merged polygons



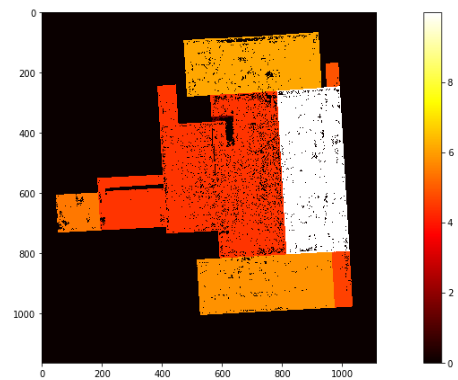
Rendered extracted 3D building model

Drone-based Generation of 3D Geometry: Process Details

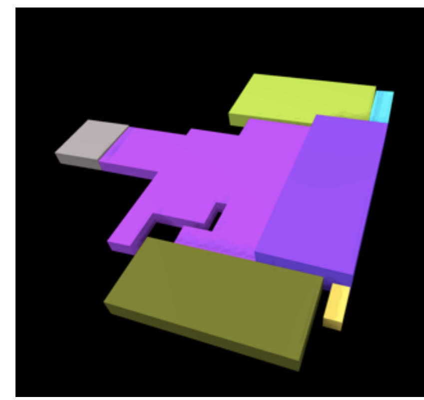
An additional example of the application of the developed algorithm to extract building 3D geometry

Shows replicability of the algorithm

3D Point clouds
Photogrammetry



Estimated heights of merged polygons

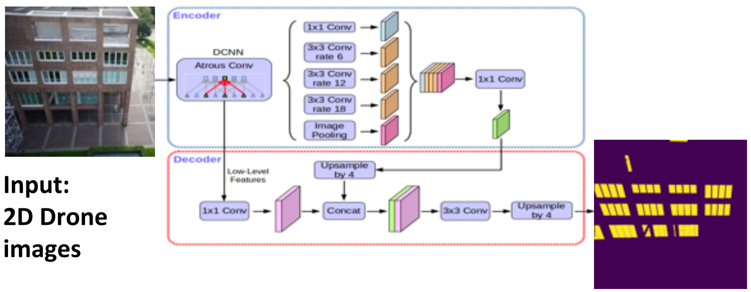


Rendered extracted 3D building model

Second building from Alameda Naval Air Station

Estimating Window-to-Wall Ratio: Work in Progress

Neural Network Architecture: DeepLab V3+

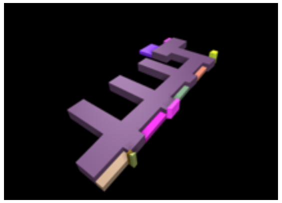


Input: 2D Drone images

Output: Windows Mask

Machine learning segmentation approach used to detect windows on the 2D images captured by drones

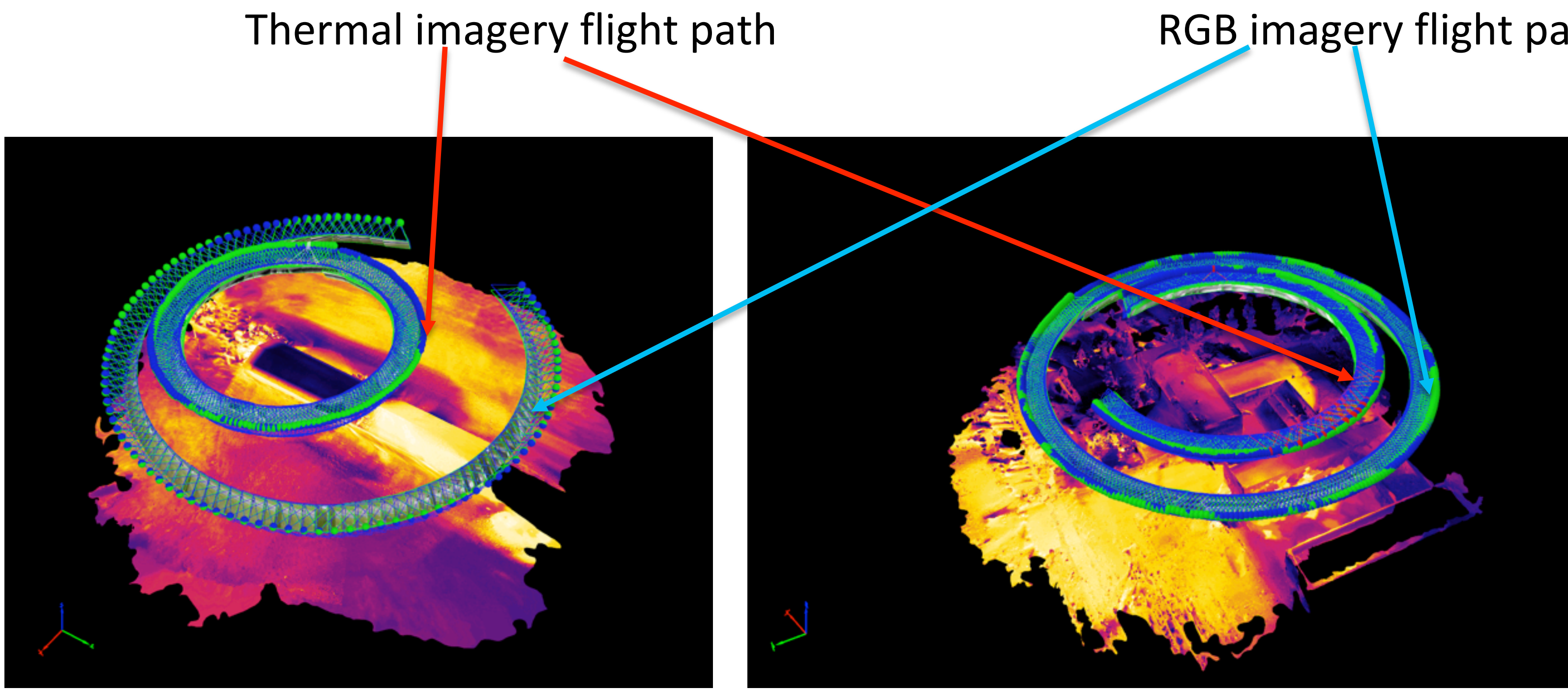
Project the windows mask on the 3D building model using the metadata provided by the photogrammetry algorithm, i.e., each pixel of the 2D image has a corresponding point in the 3D point cloud



3D building model

Estimate the window to wall ratio using the 3D geometrical information i.e., wall area and window area

Drone-based Thermal Data Capture: Work in Progress



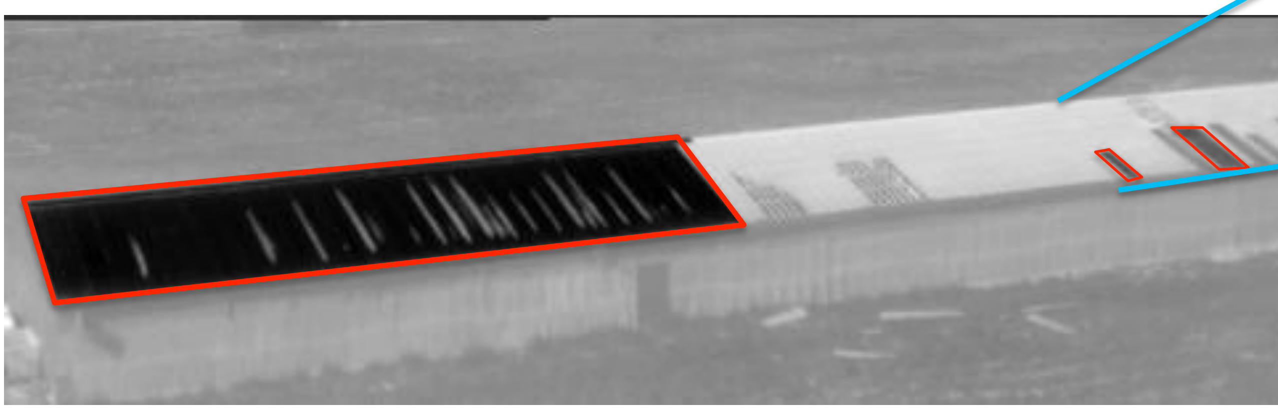
RGB and Thermal Camera View for UC Berkeley Campus Richmond Field station. (Approximately 200 thermal images and 140 RGB images have been captured)

RGB and Thermal Camera View for Alameda Naval Air Station. (Approximately 400 thermal images and 300 RGB images have been captured)

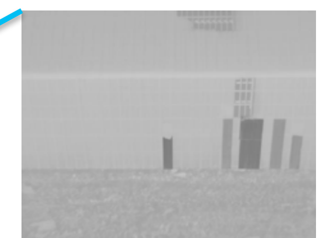
- Because of the low resolution of the thermal camera (in comparison to the RGB camera), the circular path for thermal images capture has a significantly smaller radius (25% / 30% smaller)
- In order to have an accurate 3D reconstruction of the thermal envelope, the successive images' overlap need to be higher (i.e., 90 %)

Computer Vision Workflow to Detect Envelope Thermal “Anomalies”: Work in Progress

Regions of the roof that have similar roof sheets material (confirmed with a closer look of the roof using the drone) with a different heat retention property than the rest of the roof



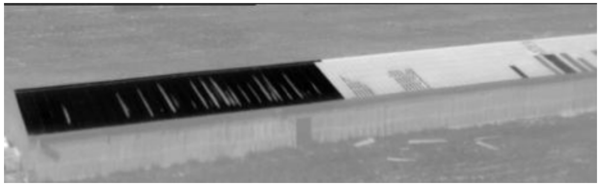
Thermal image



A top view captured by drone (thermal)

The region of interest are detected by the thermal camera as significantly cooler than the rest of the roof in the thermal images

Computer Vision Workflow to Detect Envelope Thermal “Anomalies”: Work in Progress



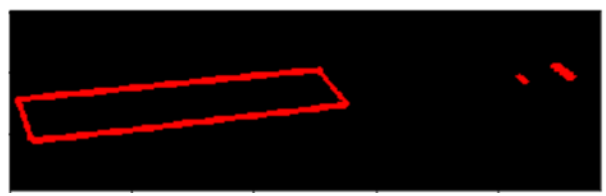
Thermal image

Apply Binary threshold

In the binary thresholding, each pixel is compared with the threshold value. If the pixel value is smaller then the threshold it is set to 0. Otherwise it is set to 1

Apply morphological image processing

The applied binary morphological operations (i.e., dilatation then erosion) aim to smooth the object boundaries, remove small objects, and close holes and gaps

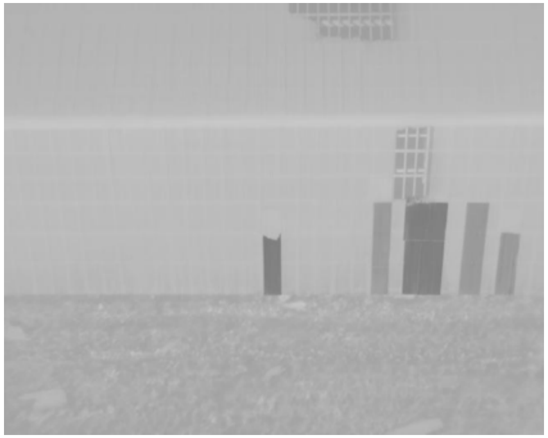


Extract the contours of the detected objects

Superimpose the detected envelope anomalous regions on top of the thermal image

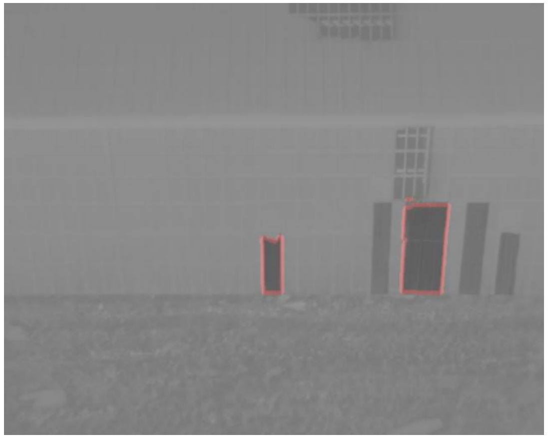
Computer Vision Workflow to Detect Envelope Thermal "Anomalies": Work in Progress

Application of the workflow on a top view image (closer view = higher resolution)



Top view of the roof thermal image

Detected thermal anomalies after applying the binary thresholding and morphological image processing



Superimposition of the detected anomalous regions and the thermal image

Closer view of the envelope provides more accurate thermal anomalies detection due to the higher resolution of the images. This will be particularly important for windows thermal leaks detection

Summary of Outcomes

- Open-source Automated Building Footprint Extractor (AutoBFE) available on Github
- Quantitative and qualitative comparison with state of the art openly available foot print data source (i.e., Microsoft foot prints)
- Developed accurate and automatic algorithm for extraction of 3D Geometrical buildings characteristics.
- Developed a preliminary workflow to extract windows to wall ratio
- Established the foundation of the drone thermal images capture and processing
- Developed a preliminary computer vision approach to detect thermal anomalies in the building's envelope.
  - Initial results show that the quality of the captured thermal images (i.e., resolution of the images) provide a good foundation for relatively accurate detection of thermal anomalies that can occur on building's envelope

Next Steps

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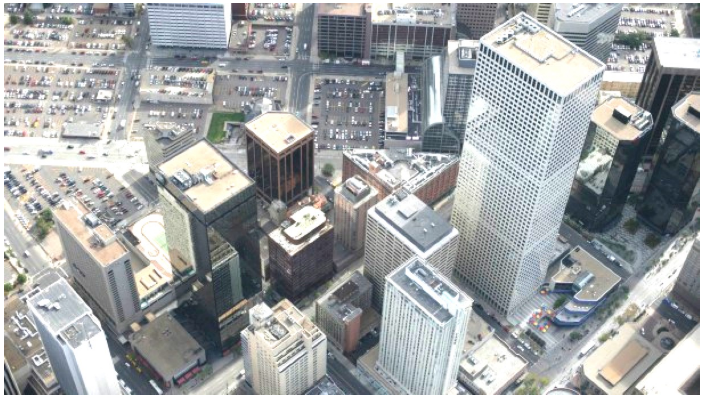
R&D Look-ahead

- Drone imagery
  - Improve machine learning segmentation of windows for more accurate window to wall ratio
  - Enhance thermal imagery capture and processing for more accurate thermal 3D model
  - Develop robust computer vision workflow to detect envelope's thermal anomalies
    - generalizable to different type of leaks, e.g. water infiltration, thermal bridges
  - Develop toolkit with methods, publish as open source

- Explore new data sources
  - LIDAR, e.g. for bldg. height from aerial images
  - Oblique images, e.g. for façade characteristics



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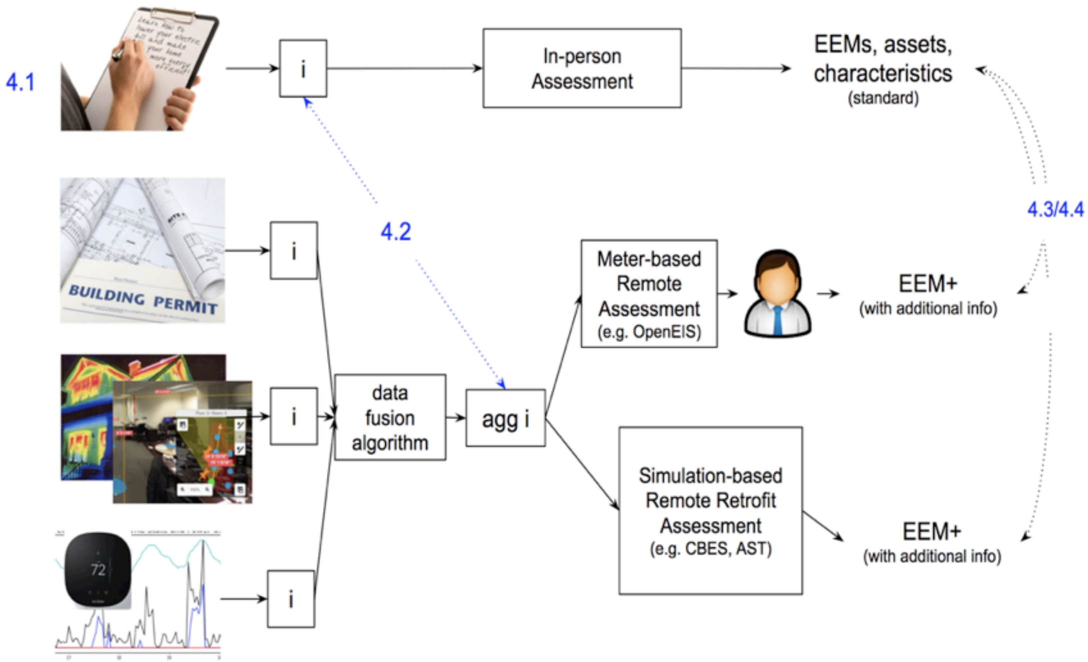
Testing and Evaluation

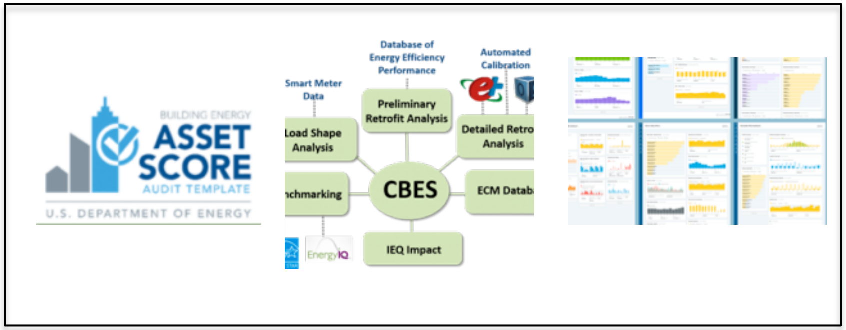


- Improved EE measure identification
- Cost-effectiveness
- Reduced labor time

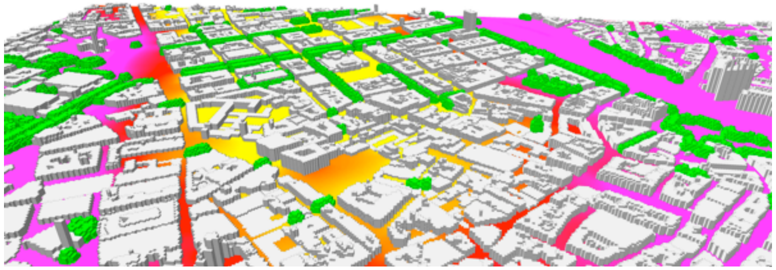
Compared to conventional building audits, tools, and EMIS

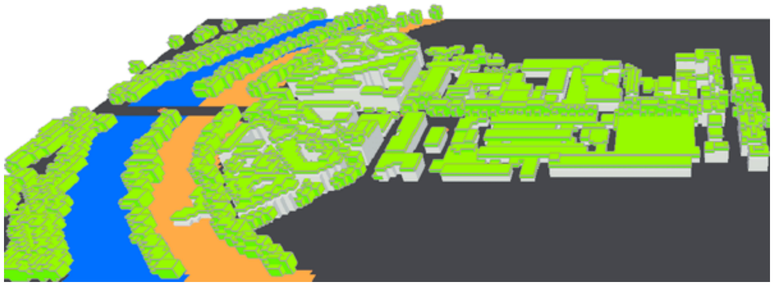
Primary and Secondary Applications

- Primary, initial focus: Bldg. developers and users (owners, operators, EE service providers) of existing simulation-based and data-driven analytics tools
  - Enhance outputs by providing new/improved inputs



- Emergent secondary focus: Beyond bldgs. campus and city asset managers, architects, urban designers and planners
  - Enhance buildings outdoor asset identification, classification, and labeling
  - Site and track distributed energy resources (DERs)
  - Plan the hardscape: vegetation ratio, cool surfaces, water bodies
  - Provide exterior "time series" or seasonal image data capture





Thank you

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Reshma Singh

reshmasingh@lbl.gov

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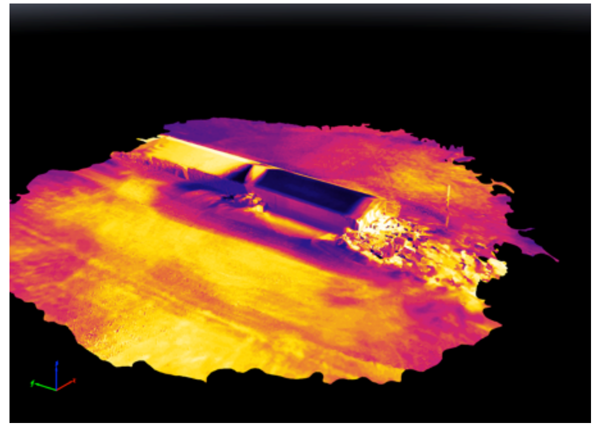
Appendix

Photogrammetry Processing Steps (Using Pix4D)

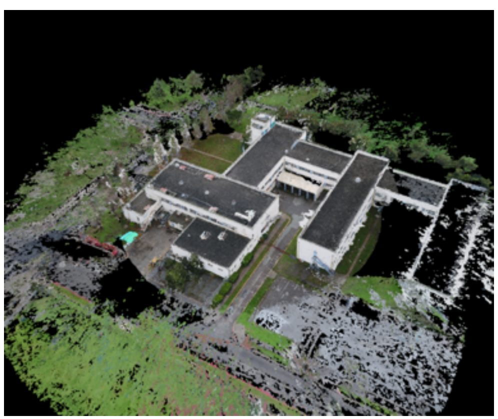
UC Berkeley Campus Richmond Field station

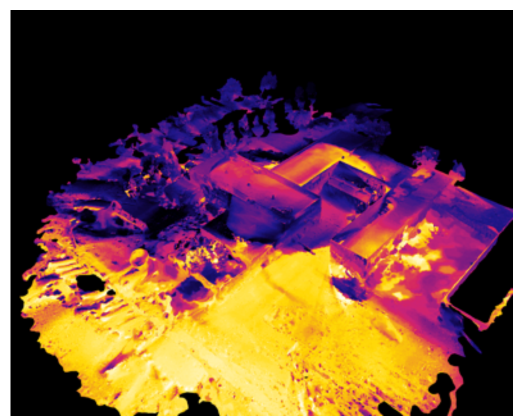


RGB points cloud output

3D Mesh, texture mapped with thermal imagery

Alameda Naval Air Station



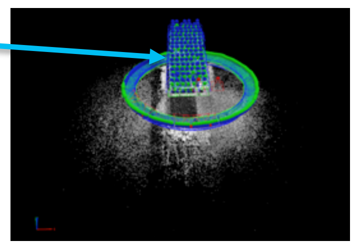


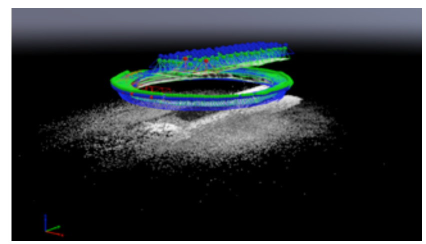
Drone-based Thermal Data Processing: Work in Progress

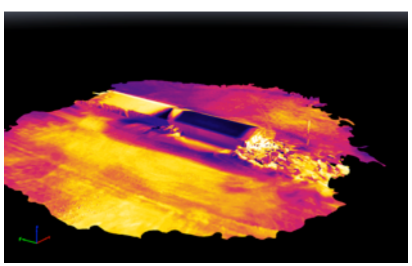
Improve the quality/accuracy of the 3D thermal reconstruction

- Tuning Pix4D photogrammetry parameters
- Testing additional flight trajectory for data collection (e.g., additional flight to capture roof top view images)

Top down view data capture using grid-type flight path

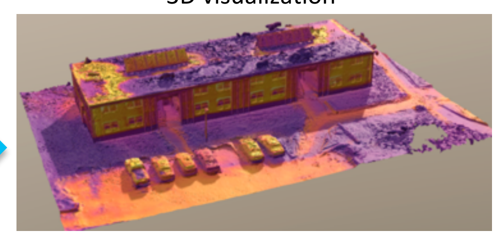






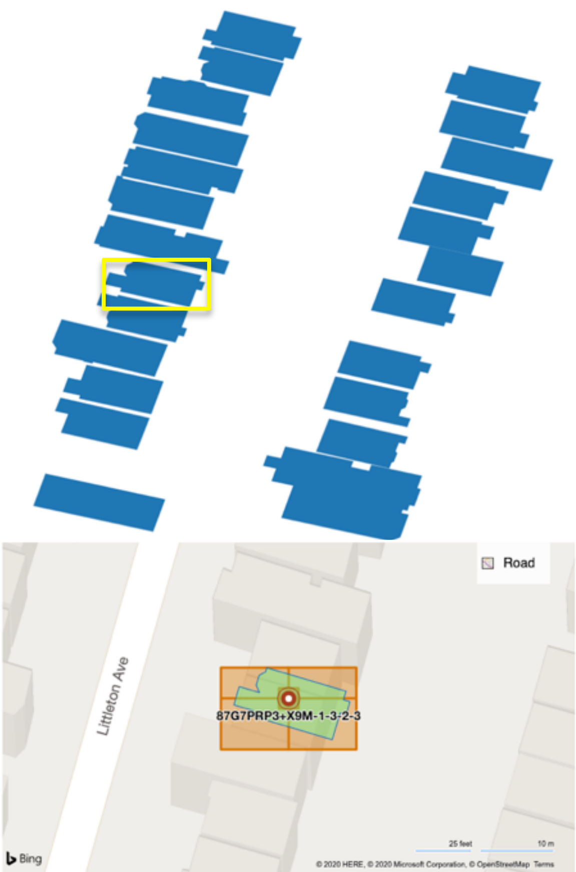
The goal is to visualize more details in the 3D thermal representation

Example of a more accurate thermal 3D visualization

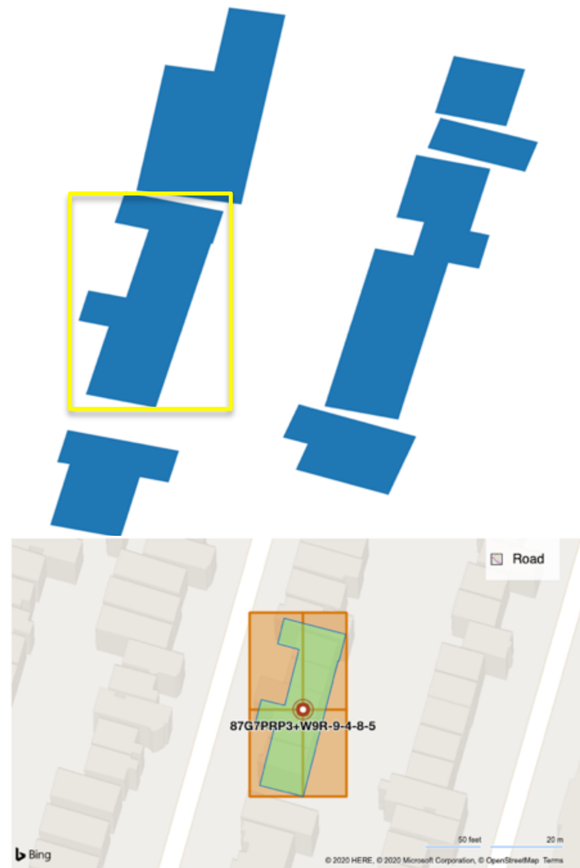


UBID Comparison

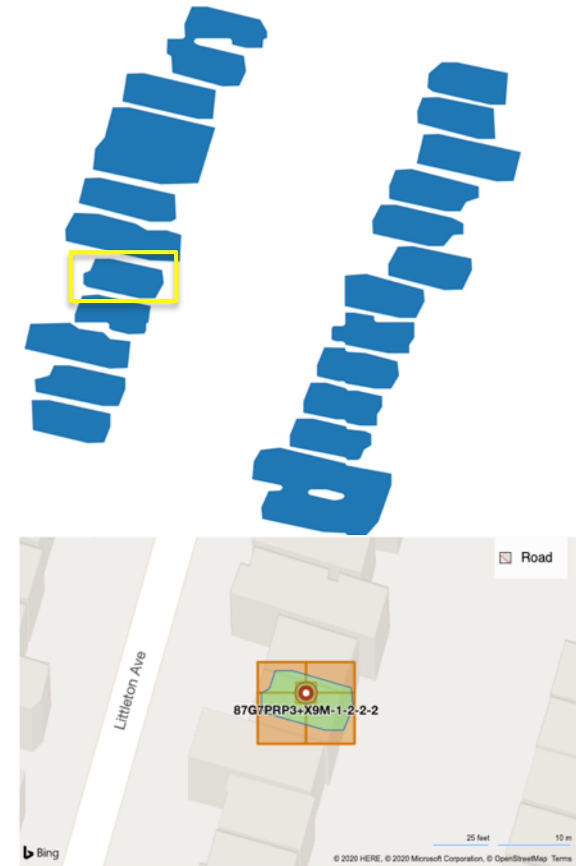
Example 2



Actual



Microsoft



Our Prediction

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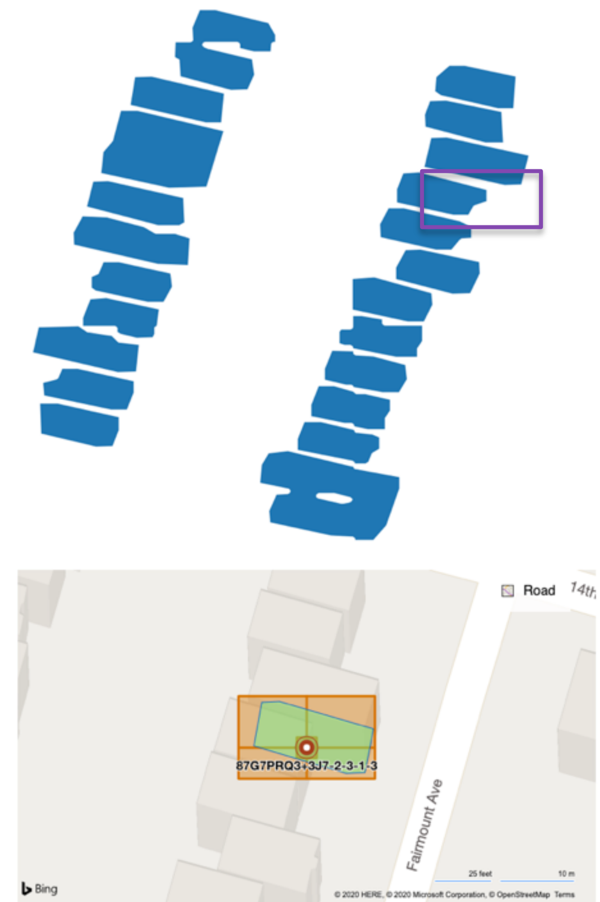
UBID Comparison

Example 3

Actual

Microsoft



Our Prediction