Paper Session 6: Urban and Community Scale Modeling

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Using Measured Building Energy Data to Infer Building Type For Urban Building Energy Modeling

Learning Objectives

1. Describe how measured energy use can be used to infer building prototype at an urban scale.
2. Compare various methodologies for evaluating time series similarity for building energy use at multiple temporal resolutions.

Acknowledgements

- Department of Energy, Building Technologies Office
- Co-Authors
  - Evan Ezell
  - Joshua New

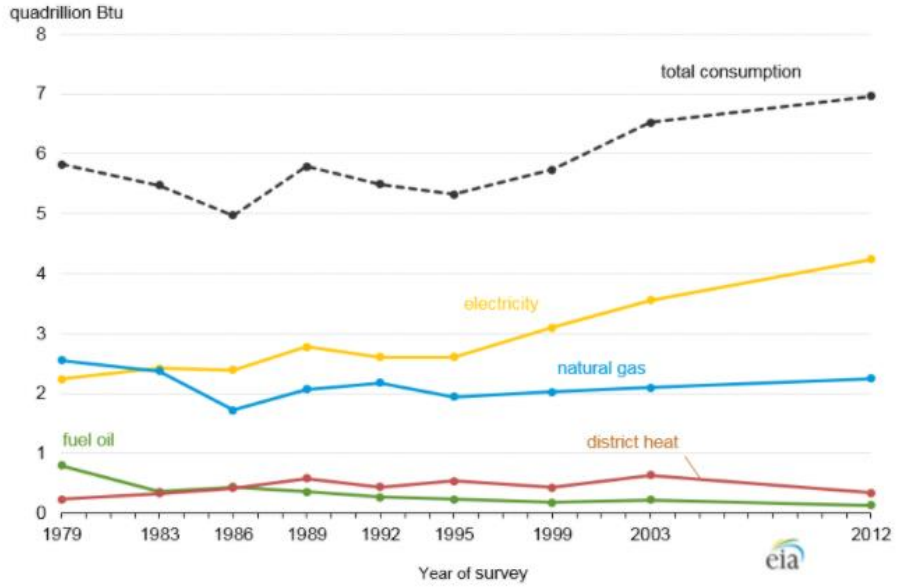
Outline/Agenda

- Motivation
- Background
  - Building Energy Modeling
  - AutoBEM
- Methodology
  - Method selection and implementation
- Results
  - Building type assignments
  - Uncalibrated CVRMSE values
  - Classification distance vs CVRMSE
- Conclusion

Motivation

- Energy usage increasing in United States
- Buildings use about 40% of energy in the US
- Modeling buildings is important to efficiently design and optimize buildings and building related systems

Figure 1. Total electricity usage has increased more than the other energy sources since 2003



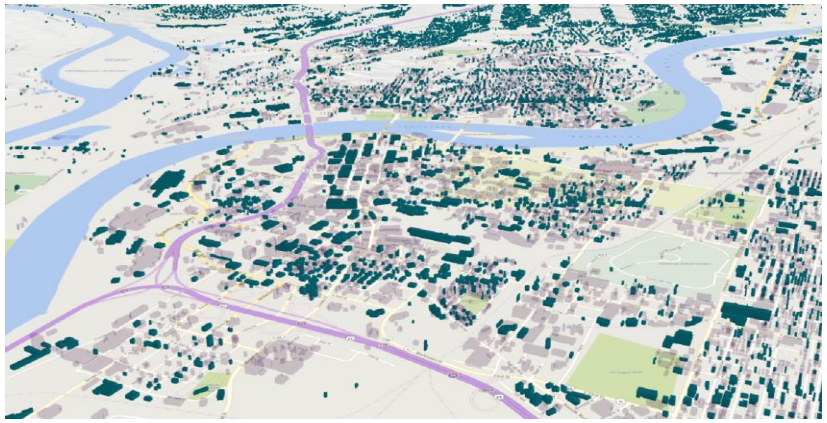
Source: U.S. Energy Information Administration, Commercial Buildings Energy Consumption Survey

Building Energy Modeling

- Add notes on BEM and EnergyPlus here
- EnergyPlus is Department of Energy's flagship building energy simulation tool
  - Uses thousands of building properties as input
  - Physics-based simulation to estimate energy use
  - Typically used for individual buildings

AutoBEM

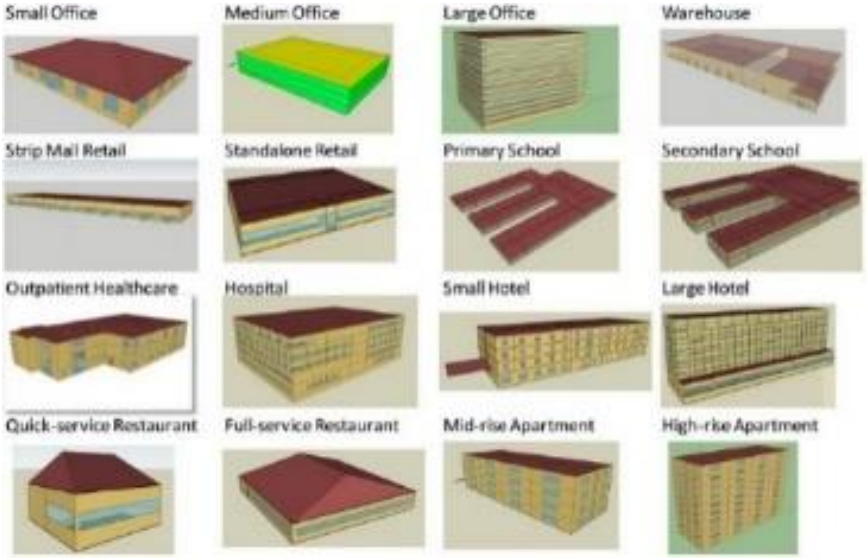
- AutoBEM
  - Automatic Building Energy Modeling
- Built in python on top of EnergyPlus for scale
  - Simplifies thousands of inputs necessary to data available at large scale
    - Building geometry (semantic segmentation)
    - Building height (lidar)
    - Building type (various)
    - Building age (various)
- More than 1M buildings per hour on Supercomputing resources (THETA – Argonne National Lab)



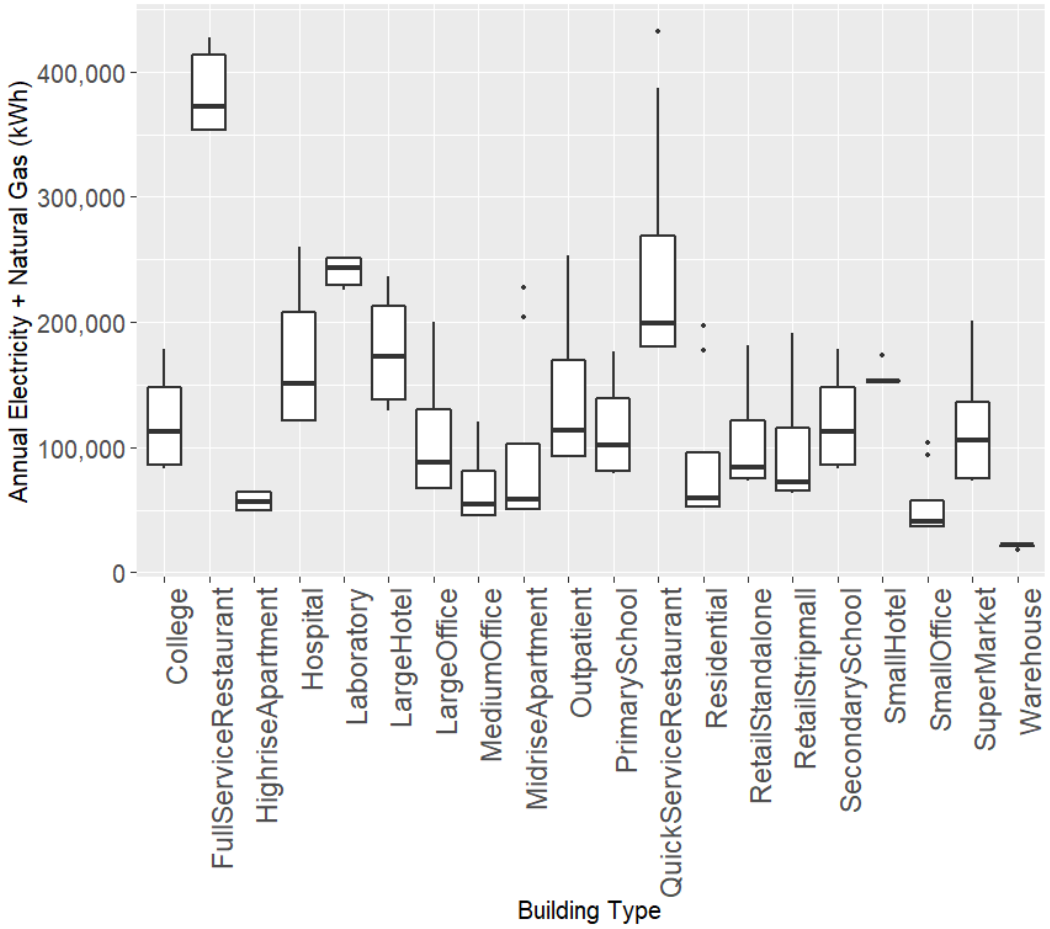
Bass, Brett and New, Joshua, and Copeland, William (2020)

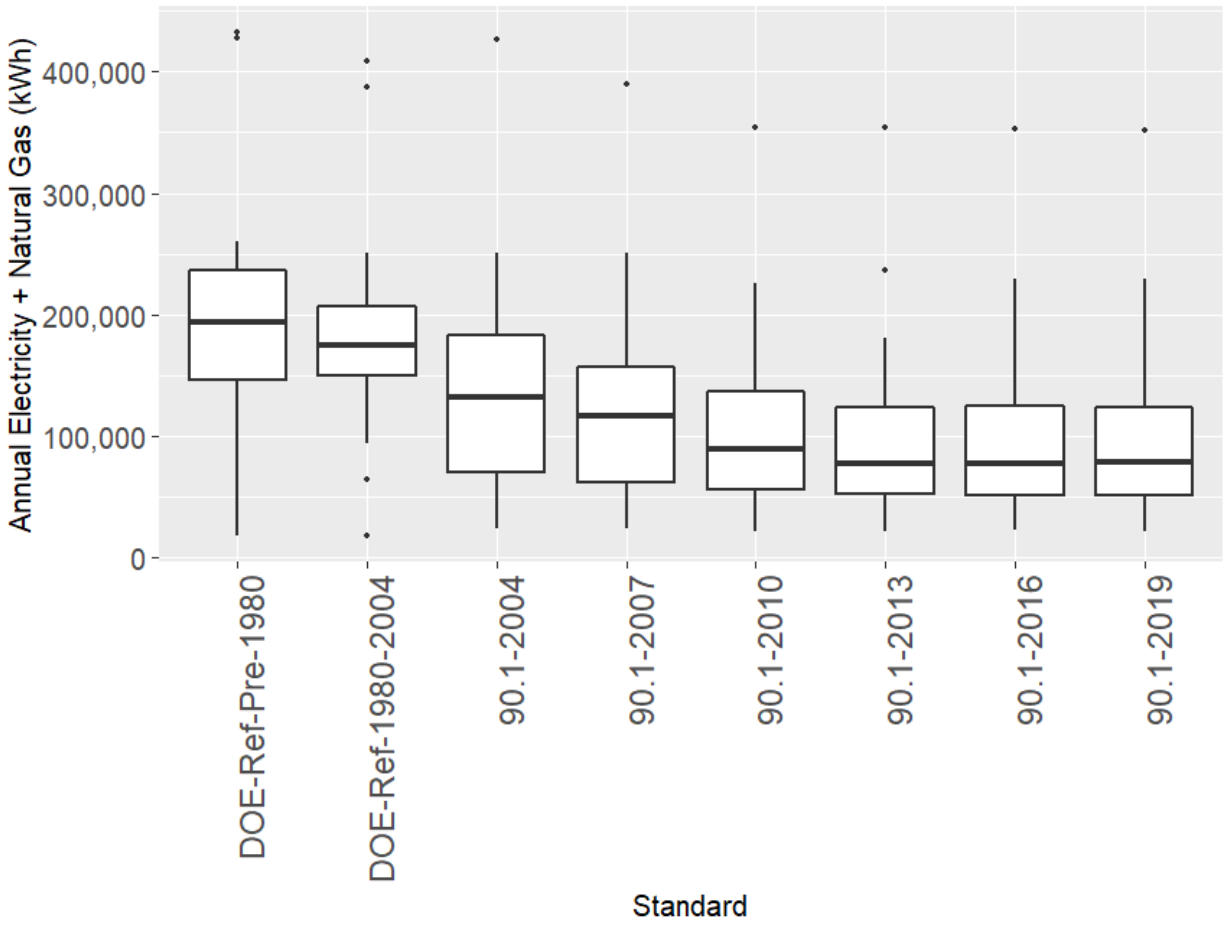
Building Metadata Aggregation

- Building Geometry
  - OpenStreetMap
  - Semantic Segmentation
- Building Height
  - Lidar
  - JAXA
- Building Type
  - Tax assessors' data
  - Land use data
  - Point of Interest Data
  - **Comparison to measured data**
- Building Age (Vintage)
  - Tax assessors' data
  - GAIA urban sprawl data
  - **Comparison to measured data**



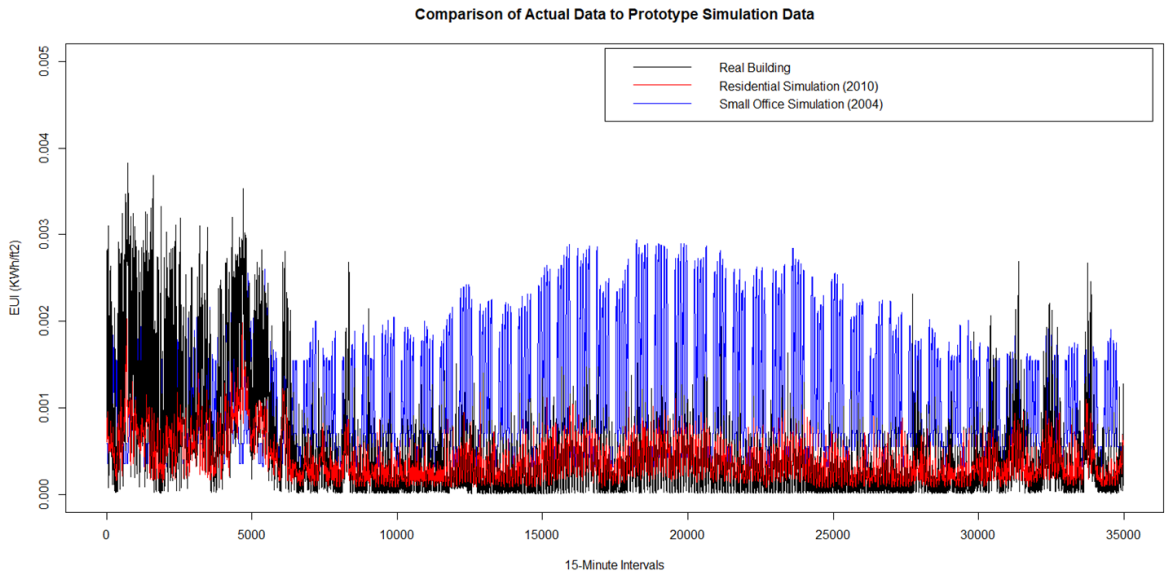
Building Type Energy Impact





Comparison to Measured Data

- Electric Power Board of Chattanooga
  - Shared 15-min smart meter electricity data for ~178k meters
- Can we assign building type based on measured building energy data?
- Compare measured energy use to prototype simulation results for same year



Comparison to Measured Data

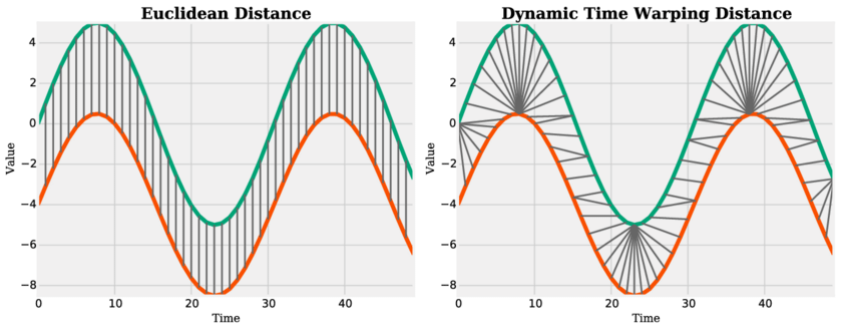
- Each real building Energy Use Intensity (EUI) is compared to each of the prototype building/vintage combinations
- Three methods considered for comparing the time series
  - Euclidean Distance
  - Dynamic Time Warping
  - Pearson Correlation (discarded based on preliminary results)

Building Type	Standard
Small Office	DOE-Ref-Pre-1980
Medium Office	DOE-Ref-1980-2004
Large Office	90.1-2004
Standalone Retail	90.1-2007
Retail Stripmall	90.1-2010
Primary School	90.1-2013
Secondary School	90.1-2016
Outpatient	90.1-2019
Hospital	
Laboratory	
Small Hotel	
Large Hotel	
Warehouse	
Quick-service Restaurant	
Full-service Restaurant	
Supermarket	
Mid-rise Apartment	
High-rise Apartment	
Residential	

Comparison Methods

- Euclidean Distance
  - Straightforward method
  - No imputation required
  - Low computational cost
- Dynamic Time Warping
  - Imputation required
  - High computational burden
  - Temporal offset pattern recognition
- Run at both hourly and monthly temporal resolution

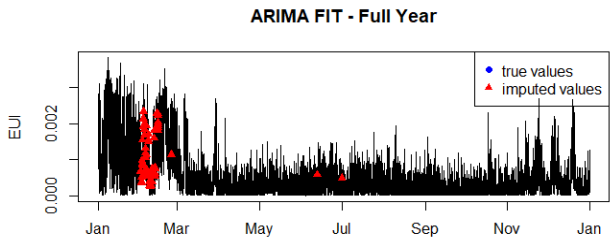
$$EucDist = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

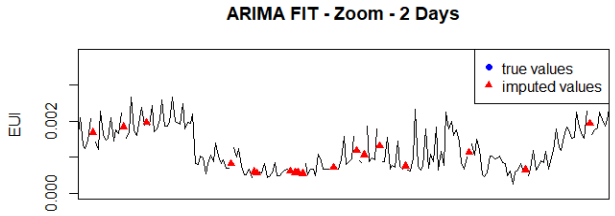


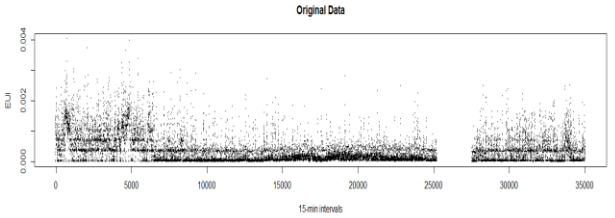
Schfer, P. (2015).

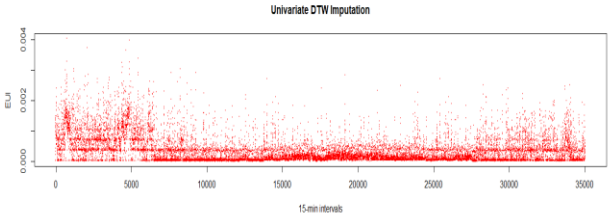
Imputation

- Small Gaps (< 1 week)
  - ARIMA
- Large Gaps (>1 week)
  - Univariate Dynamic Time Warping
    - Replaces missing data gap with most similar subsequence to sequence before gap
- Mostly missing (> 75% missing)
  - Removed from dataset









Results

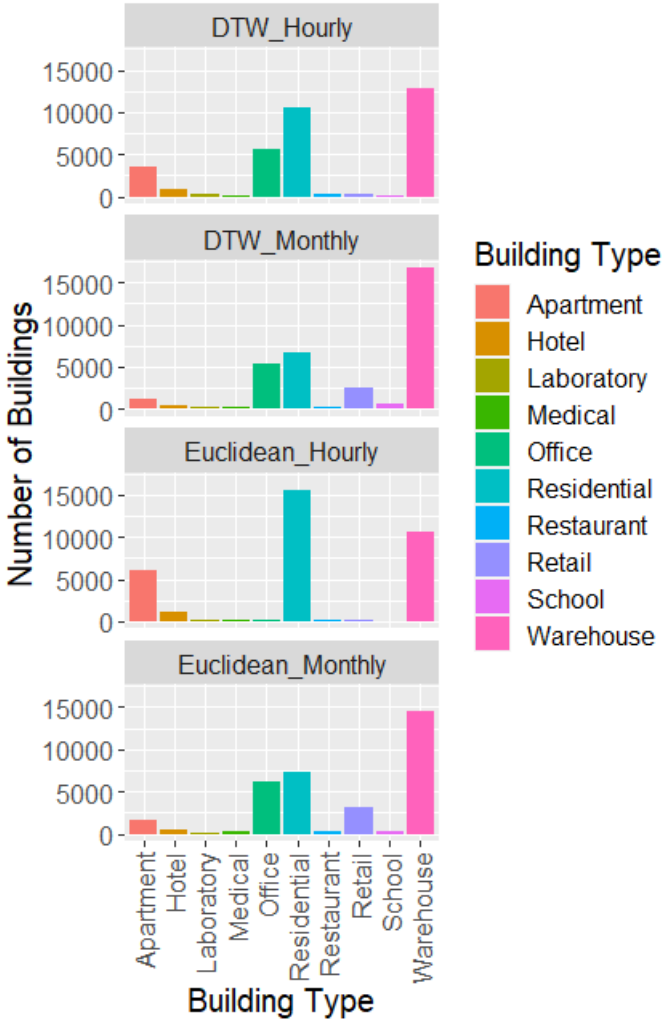
- Methods were evaluated on more than 50 thousand buildings in Chattanooga, TN
- Evaluated using monthly and hourly CVRMSE
- Baseline AutoBEM models were compared to measured data
  - Models were not further improved/calibrated as they typically would in analysis
- Actual building energy use may not always match building function

Computational Burden

- Time to classify building
  - Euclidean Distance – 0.117 sec
  - Dynamic Time Warping 133.5 sec

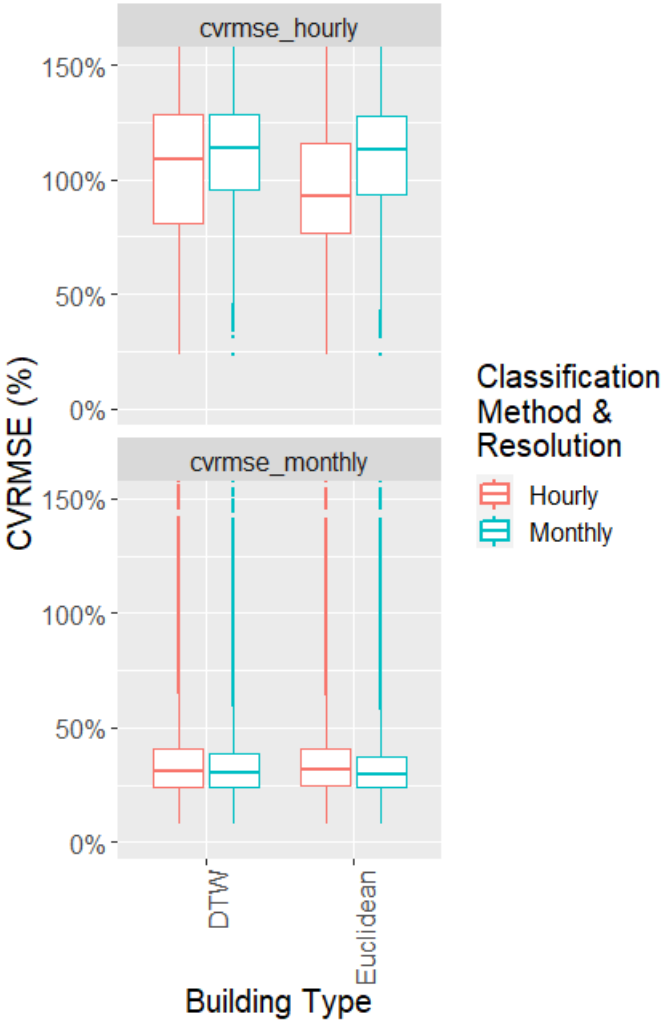
Method Classifications

- Most common building types
  - Residential
  - Offices
  - Warehouses
  - Retail
  - Education
  - Food Service
  - Food Sales
- Warehouses have lowest prototype EUI

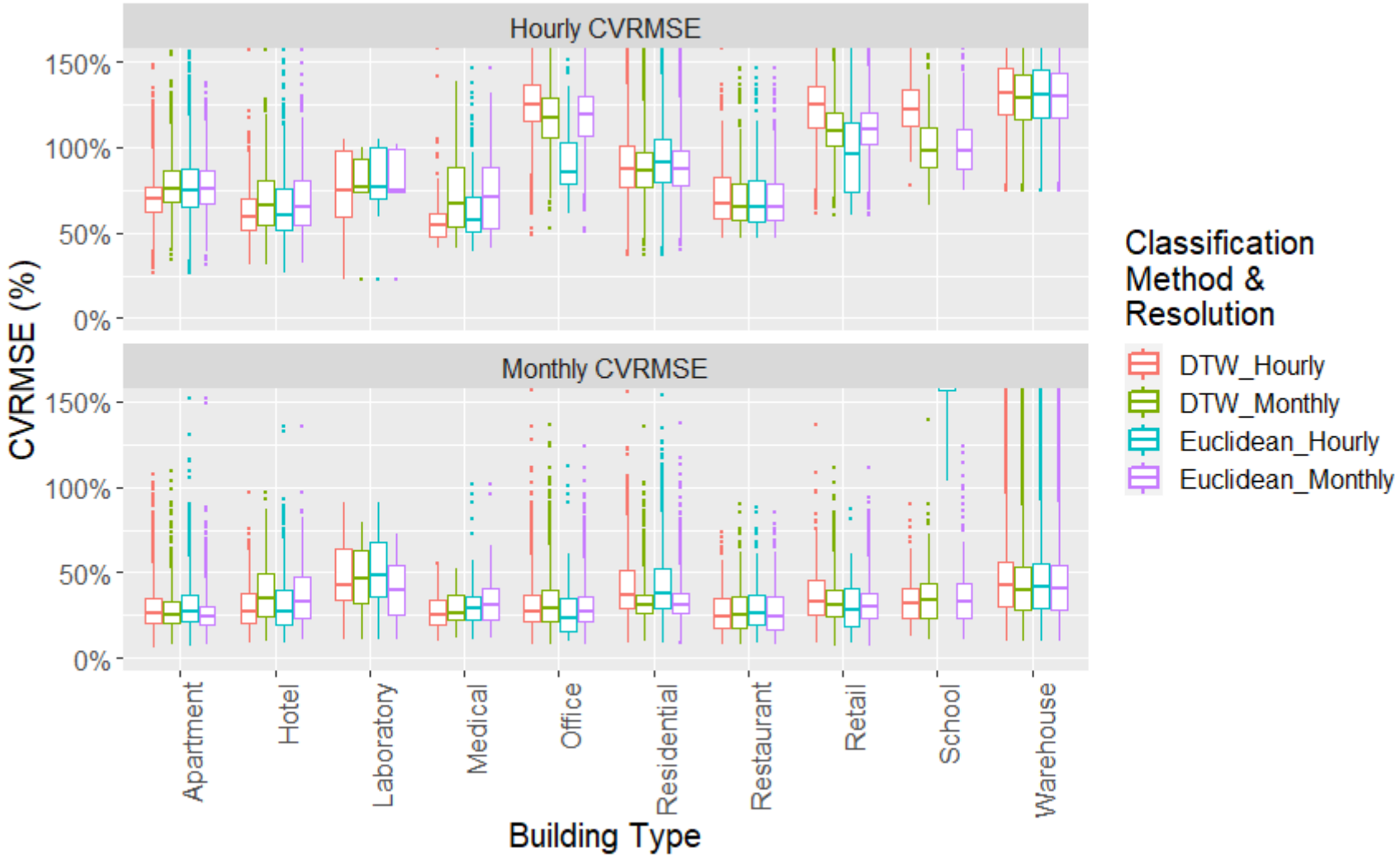


Classification Results

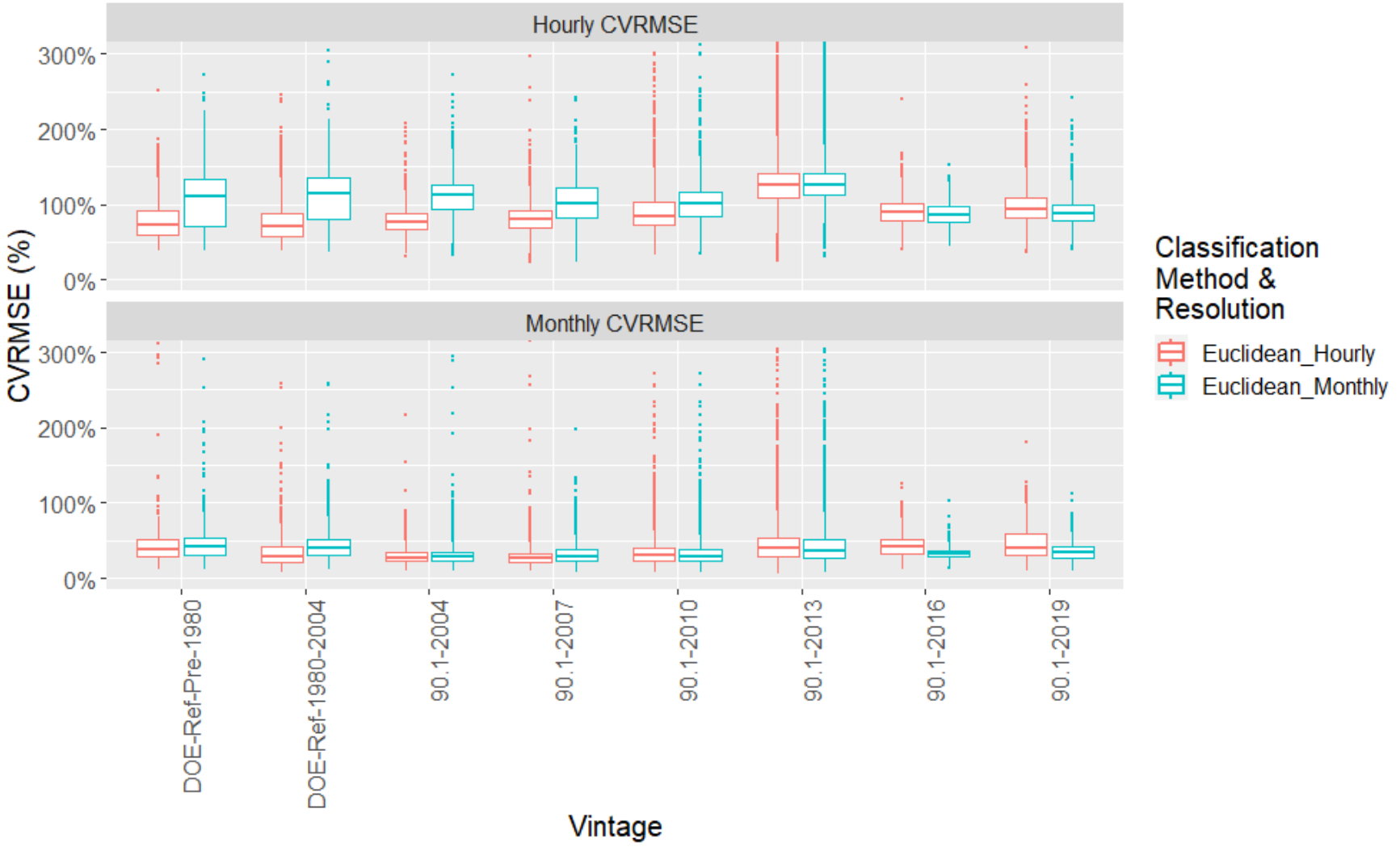
- Uncalibrated results – require further calibration
- Calibrated model
  - Hourly CVRMSE < 15%
  - Monthly CVRMSE < 30%



Classification Results (Building Type)

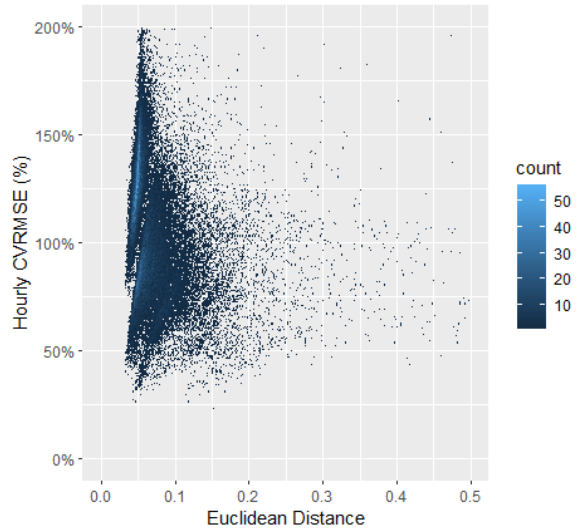


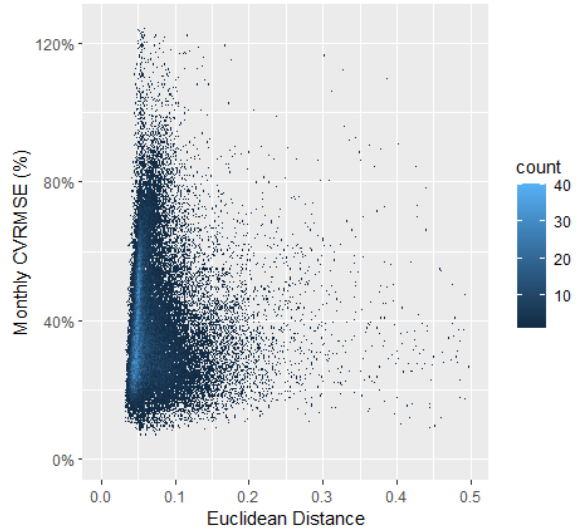
Classification Results (Vintage)



Classification Distance vs CVRMSE

- Correlation between classification distance and CVRMSE?
- No major correlation
- Different pattern between monthly and hourly CVRMSE





Conclusions

- Measured data can be used to assign building type for large scale building energy modeling analyses
- Data cleaning methodology is a critical step when dealing with measured building energy data
- The necessary temporal resolution of measured data for the analysis depends on the analysis aims
- The benefits of Dynamic Time Warping to not outweigh the computational burden of the method for this use case

Bibliography

Bass, B., Ezell, E., & New, J. (2022). Using Measured Building Energy Data to Infer Building Type For Urban Building Energy Modeling. Presented at the 2022 Building Performance Analysis Conference and SimBuild, Chicago, IL, September 14-16.

QUESTIONS?

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