

Leveraging earth observational data to assess the impact of microclimates on Urban Building Energy Models (UBEMs): A data-driven case study in Seattle, Washington

Amanda Worthy¹, Narjes Abbasabadi², Mehdi Ashayeri³

¹ Department of Civil and Environmental Engineering, University of Washington

² Department of Architecture, University of Washington

³ School of Architecture, Southern Illinois University

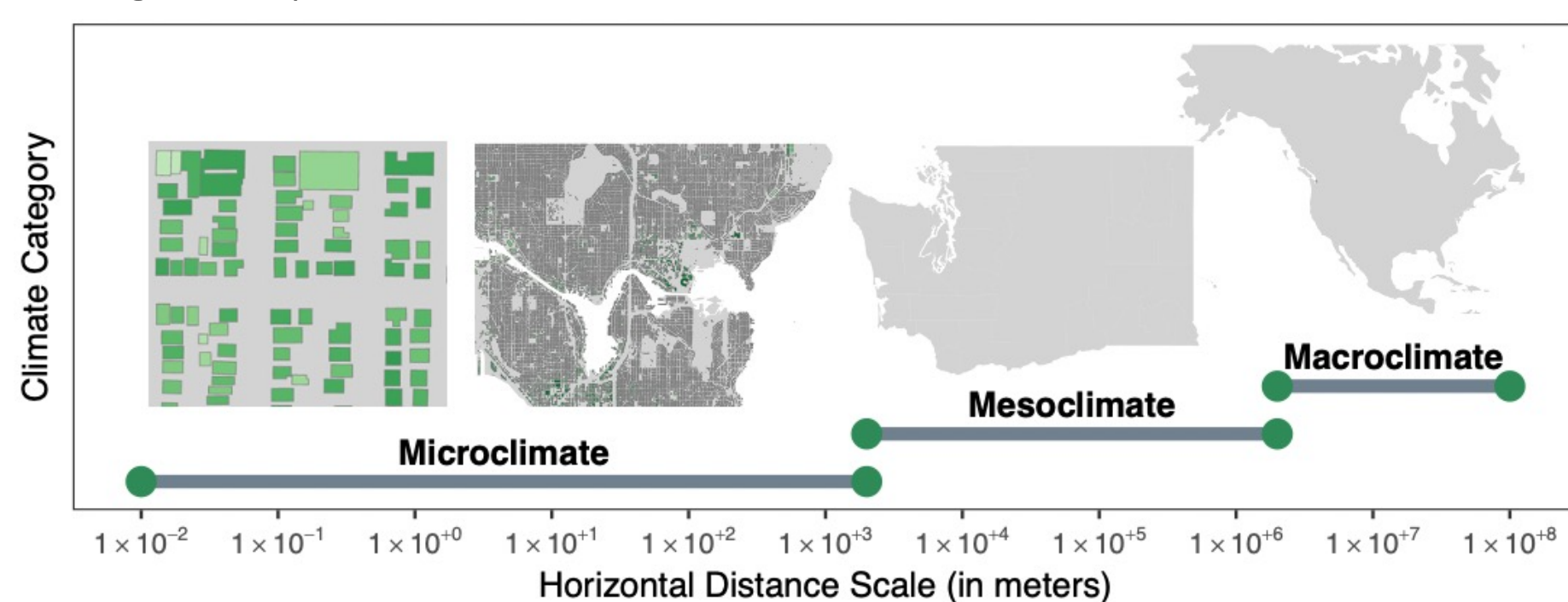
Research Objective

Current urban building energy modeling methodologies and tools are limited by their non-urban specific and aggregated climate data inputs, leading to discrepancies between modeled and actual energy expenditures. This research develops a data-driven methodology to better access the impact of microclimates on urban building energy models. It utilizes open-source datasets and applies the approach to a case study in Seattle, Washington, USA.

1. Introduction

- Urban building energy modeling provides an essential understanding of energy system operations for a cluster of buildings and by identifying resource use pattern for these structures.
- Urban building energy modeled errors are exacerbated in cities due to urban microclimate conditions and the urban heat island effect.
- Urban microclimates are characterized by differences among urban areas outdoor climate, surface temperature, humidity, cloud coverage, solar radiation, windspeed, and wind direction, as referenced with the rural conditions in similar geographical areas.

Figure 1: Spatial scale of climates



2. Research Questions

- How can earth observational data be used in a data-driven urban building energy modeling approach to more accurately assess the impact of urban microclimates on energy demand and performance calculations?
- What earth observational environmental parameters are most important for final annual electricity consumption prediction?
- How do conventionally used Typical Meteorological Year 3 (TMY) environmental observations and earth observational environmental measurements compare?
- Can earth observational sampling procedures be improved to better provide for urban energy performance studies?

3. Methodology

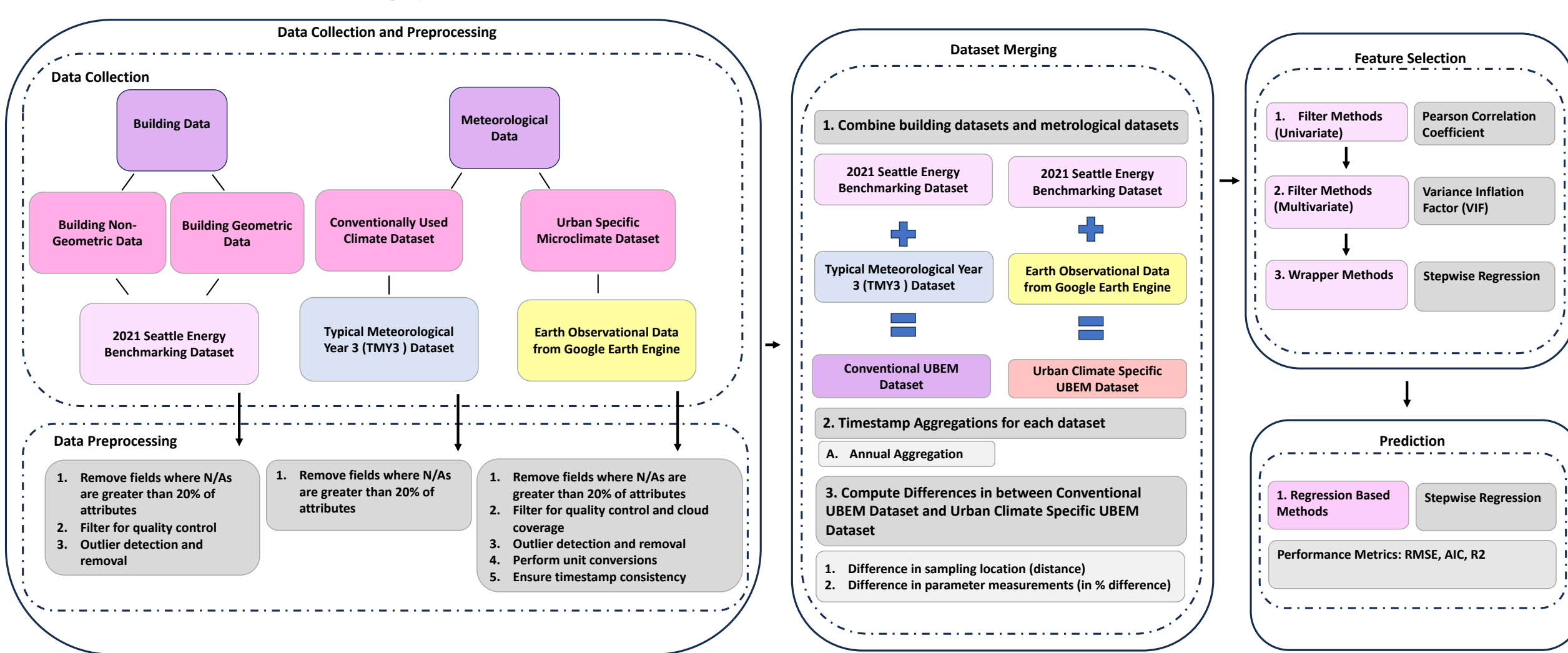


Figure 2: Workflow for Phase 1 of the project, as highlighted in this poster

Data collection and screening:

- Building Energy Data:** Annual energy consumption observations and building characteristic data were obtained for 2026 buildings larger than 20,000 square feet in Seattle, Washington in 2021 from the Seattle Energy Benchmarking Dataset (EB) [1].
 - Urban Specific Weather and Microclimate Data:** The Google Earth Engine (GEE) Dataset Catalogue (as of 01/2024) was screened for earth observational measurements and reanalysis products relevant to urban microclimates. If screening criteria was met, then 2021 observations were sampled at each (2026) building location (given by longitude and latitude from the Energy Benchmarking dataset) using an automated approach. Then, observations for each environmental parameter, sampled at each building location, were combined and merged to embody the "urban specific weather and microclimate" dataset.
- Screening criteria includes:
- Observations taken in 2021
 - Observations taken over Seattle and CONUS
 - Spatial resolution less than 2.5 km
 - Temporal sampling frequency higher than 30 days
 - Environmental parameters must be related to urban microclimates
 - Meet quality assurance standards (limited N/As)

- Conventional Climate Dataset:** Typical Meteorological Year 3 [3] weather data was obtained for the Seattle-Tacoma International Airport Weather Station and used to facilitate comparison between microclimate and existing urban building energy modeling methodologies.

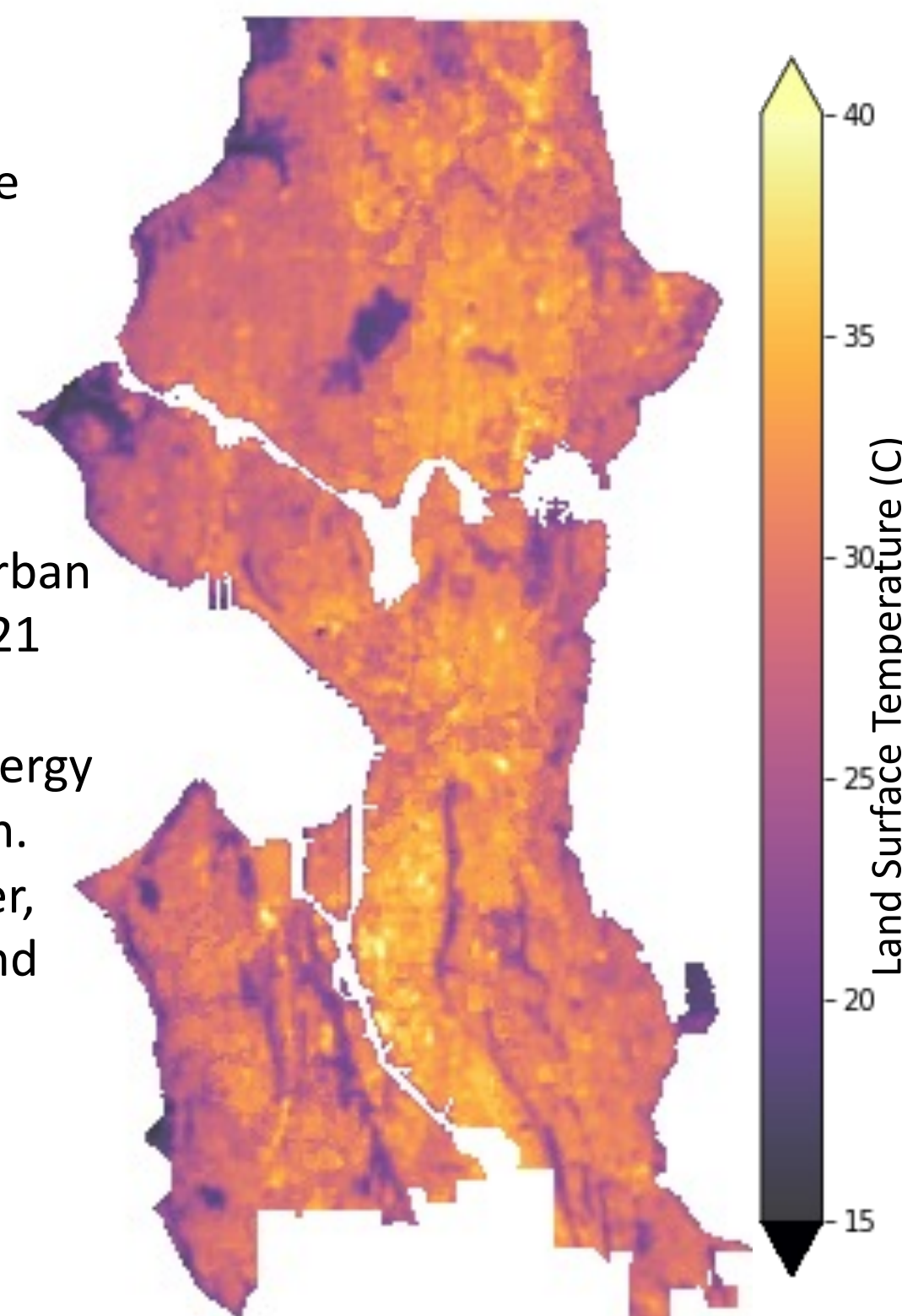


Figure 3: Average Seattle Land Surface Temperature in 2021, Data Source: LANDSAT 8 Level 2, Collection 2, Tier 1 [2]

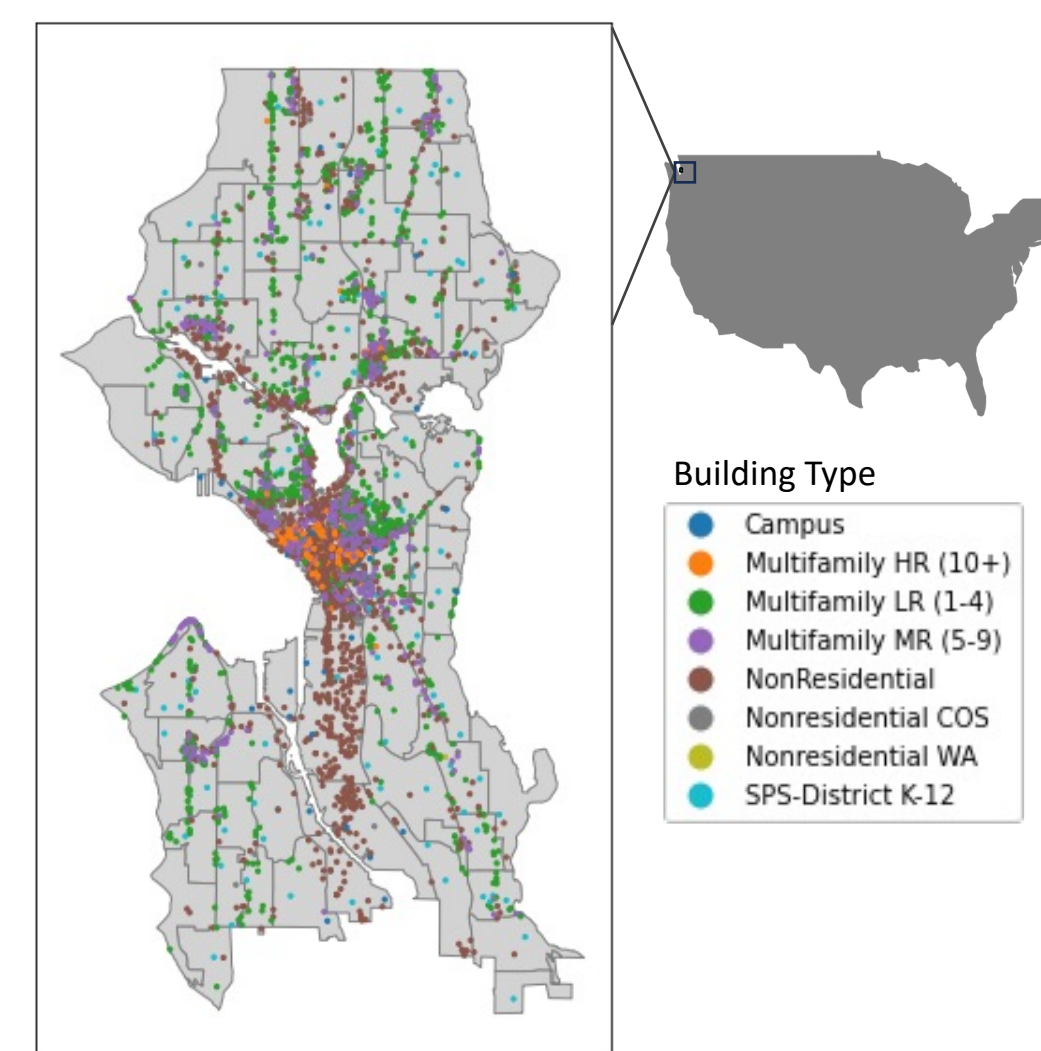


Figure 4: Buildings examined in the Seattle Case Study, Data Source: Seattle Energy Benchmarking Dataset

Sensor	Available Products	Spatial Resolution	Temporal Resolution
USGS LANDSAT 8 Level 2, Collection 2, Tier 1	Ultra Blue, Blue, Green, Red, Near Infrared, Shortwave Infrared, Surface Temperature, Atmospheric Transmittance, Downwelled Radiance, Upwelled Radiance	30 m	16 days
NOAA RTMA	Elevation, Pressure, Temperature, Dew Point Temperature, Wind Speed, Specific Humidity, Wind Direction, Wind Speed (gust), Visibility, Cloud Cover, Precipitation	2500 m	Hourly
Sentinel-5P NRTI	Aerosol Index, Aerosol Height, Carbon Monoxide, Formaldehyde, Nitrogen Dioxide, Ozone, Sulfur Dioxide	1113.2 m	Hourly
USGS National Landcover Database	Landcover	30 m	2021 instance
USFS Tree Canopy Cover v2021-4	Tree Canopy Cover	30 m	2021 instance
NASA DEM	Digital Elevation	30 m	2000 instance

Table 1: Screened Google Earth Engine Earth Observational Microclimate Dataset Products used for analysis in this study

4. Preliminary Results

- The most influential building and earth observational microclimate environmental parameters for final annual electricity consumption prediction were identified through Pearson Correlation Coefficient and Variance Inflation Factor (VIF) analysis. Then, stepwise regression was performed.
 - Feature selection includes:** RTMA Total Cloud Cover (%), LANDSAT 8 Ultra Blue Surface Reflectance, LANDSAT 8 Land Surface Temperature (c), LANDSAT 8 NDVI, Building Type, Number of Floors, Number of Buildings on Property, Year Built, Building(s) Gross Floor Area (sqft), and ENERGYSTAR Score.
 - Stepwise Model Performance:** Adjusted $R^2 = 0.67$
- Higher variation between TMY and earth observational measurements are observed within the denser metropolitan regions, indicating that urban microclimate conditions exist in Seattle; calling for future research to examine their interconnectivities with urban infrastructure.

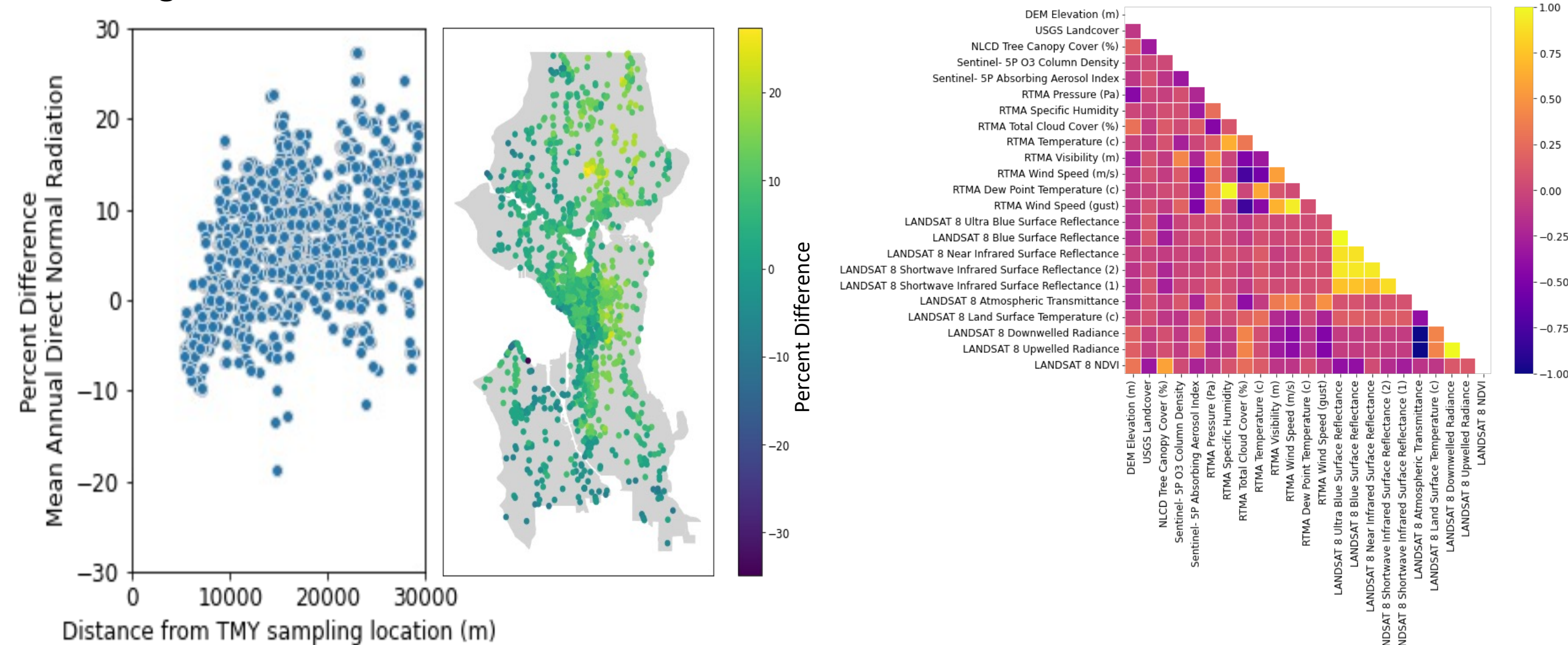


Figure 5: Mean annual direct normal radiation percent difference between TMY and LANDSAT 8 observations, and correlation to measurement sampling location distance.

Figure 6: Pearson Correlation Coefficient of Earth Observational Microclimate Data Parameters, indicating high correlation among many environmental data parameters

5. Conclusions

- Earth observational environmental data measurements have proved to be a reliable data source for further investigation of energy consumption of urban buildings.
 - Consideration should be taken to reduce uncertainties in data quality resulting from cloud cover, excessive reflection absorbance, and proximity to water bodies.
- Further Analysis in Phase 2 of this work will be taken to explore the complex relationships between variables across smaller temporal aggregations (ex: daily, monthly) using machine learning techniques

6. Bibliography

- "Data and Reports - Environment | seattle.gov." Accessed: Feb. 27, 2024. [Online]. Available: <https://www.seattle.gov/environment/climate-change/buildings-and-energy/energy-benchmarking/data-and-reports#individualbuildingdata>
- N. Gorelick, M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore, "Google Earth Engine: Planetary-scale geospatial analysis for everyone," *Remote Sens. Environ.*, vol. 202, pp. 18–27, Dec. 2017, doi: 10.1016/j.rse.2017.06.031.
- S. Wilcox and W. Marion, "Users Manual for TMY3 Data Sets," *Tech. Rep.*, 2008.

7. Acknowledgements

We would like to acknowledge the support from the National Science Foundation for organizing this poster presentation (NSF Award No. 2401864). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.