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# A Decision-Support Framework for Community Building Energy Modeling in Developing Nations, Leveraging Satellite Imagery and Machine Learning Techniques

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## Abstract

Reducing energy consumption in buildings is pivotal to reaching the global net-zero target, as buildings contribute about 40% of energy-related carbon dioxide emissions.To achieve this holistic optimization of energy consumption in the global building stock, achieving net zero energy status only for a few buildings sparsely distributed across the national landscape may not yield the desirable outcome. A nascent evolving modeling schema called urban building energy modeling tries to address this gap by strategizing retrofit strategies for buildings on an urban scale. However, implementing such frameworks is primarily limited only to developed countries because of the availability of a rich existing database of digitized building footprints, which is not the case in developing countries. This study tries to bridge this gap by developing a framework using satellite imagery and machine learning techniques for developing a community building energy model and implementing the framework on a case study from India for validation. Employing this framework can help particularly in developing countries where building footprint details are not digitally available to arrive at appropriate energy reduction strategies community-wide.

## Introduction

Buildings and construction accounted for about 36% of global final energy consumption and 37% of energy-related $CO_2$ emissions in 2020, which is high compared to other end-use sectors (United Nations Environment Programme 2021). In developing nations such as India, where the building industry accounts for nearly one-third of the nation's overall energy consumption, the observed trend is statistically comparable to other emerging economies (Tarkar 2022). Thus, a drastic intervention of energy-efficient strategies is required to meet the current national sustainability needs. Even though building regulations and standards aid in constructing energy-efficient structures, most address essentially single buildings exclusively. However, policies and recommendations from standards must expand their scope from the buildings to communities/urban and take full advantage of the energy retrofit opportunities present within the premises to aid the transition to net zero emissions in the following decades.

One of the essential inputs that are required for such urban-scale energy modeling is building footprints. Many developed countries are slowly adopting the urban scale energy modeling schema because of the availability of digitized building footprint datasets, which is not the case in developing countries (Agugiaro et al. 2018). Another limitation in developing countries is the presence of a diverse range of building archetypes, unlike those of developed countries, where the properties of the buildings are relatively uniform, with fewer archetypes within a single climatic zone (Fonseca et al. 2016). Thus, this research envisages developing a framework for leveraging satellite imagery and machine learning techniques for creating building footprint datasets coupled with a community-based energy modeling approach to arrive at appropriate energy reduction strategies. Such an approach puts this study in between the scale of individual physics-based and urban-scale building energy models.

## Background

Creating energy-efficient buildings is becoming one of the leading priorities for creating a net-zero future. Creating a digital model of a building and using a physics-based simulation to calculate its energy consumption is known as Building Energy Modelling (BEM), and it is the most extensively used and acknowledged technique for simulating and analyzing a building's energy performance (Rajput and Thomas 2022). Nevertheless, these standalone building energy models have two drawbacks: they can not account for the building's urban setting and thus ignore the shading effects of other structures (Ali et al. 2021; Reinhart and Cerezo Davila 2016). However, the surrounding buildings and plants significantly affect the building's thermal performance (Yu and Pan 2018). For instance, research comparing the impact of shadowing from nearby buildings on energy usage in three cities in the USA under different climate conditions using numerical simulations show that a building's yearly energy usage for heating or cooling can vary significantly depending on the shading impact, from 16.7 to 63.4% (Han, Taylor, and Pisello 2017). As a result, considering surrounding structures effectively during the energy assessment stage enhances the effectiveness of solutions and lowers uncertainty in the evaluation.

Urban building energy modeling (UBEM) techniques are gradually developing to comprehend patterns and interactions of urban-level energy use to overcome the limitations of individual building physics-based models (Johari et al. 2020). However, the current frameworks primarily serve the needs of industrialized nations whose city models are already coded according to specific standards appropriate for exchanging energy simulation data (Kämpf and Robinson 2009). Some examples of the frameworks include CitySim and SimStadt, which cater to the countries whose city models are available in the desired CityGML standard (Agugiaro *et al.*, 2018). Another method of performing UBEMs is to segregate the whole building stock into appropriate archetypes. For example, in Danish building stock research, precise energy estimates are obtained by the building physics-based models of the archetype structures (Brøgger, Bacher and Wittchen, 2019). Although such analysis can help policymakers make quick decisions, creating such models for an Indian context is difficult. Organizing the building stock based on its typology is a significant challenge. In industrialized nations, structures built within a comparable timeframe usually share similar building geometry features. However, it is challenging to categorize building facilities in developing nations under a single or particular canopy of archetypes because most differ in structure and the theory behind heating, ventilation, and air conditioning. Such default simulation exchange and templates would not be appropriate for a developing country such as India, where the available datasets are scarce. Some of India's recent attempts to create UBEMs echo the same (Nikhil Singh, Rawal and Mathur, 2020). There is no unified database from which building footprint information can be collected.

The above limitation further supplements the geographic distribution trend of existing building stock energy models developed worldwide. Even though UBEM has made significant technological strides worldwide, its influence is almost negligible in most emerging nations, particularly India. (Fennell *et al.*, 2020). A fair assessment of the building footprint area is essential for precise energy analysis to help create energy-efficient building designs. However, in the case of no availability of an existing footprint database or relevant drawing files of the buildings constructed several decades ago, a manual survey is not feasible as it will be time-consuming, labor-intensive, and prone to errors. Instead of the manual site survey, a few techniques are frequently employed to segregate building footprints with the most commonly available satellite images.

For instance, (Asuquo Enoh, Ebere Njoku, and Chinenye Okeke 2023) used images from Landsat 7 ETM + and 8 OLI to prepare land use and land cover maps to determine the rate of changes in Lagos from 2010 to 2020. The study adopted the Maximum Likelihood Classifier to classify the satellite images and track the changes in built-up areas, agricultural land, water bodies, and forest land. Using the results obtained, the study also predicted the changes between 2025 and 2030. Maximum Likelihood is one of the most commonly used algorithms for supervised classification. However, in studies focusing on a small region of interest, the proposed algorithm fails to perform as it requires a certain minimum number of pixels in each training polygon (Congedo 2022).

Another study proposed a framework to extract large-scale building extraction from satellite images of relatively lower resolution (>0.6m). The framework comprised four primary steps: scene classification, color normalization, image super-resolution, building instance segmentation, and scene mosaicking (Chen et al. 2023). Another study developed the vision transformer networks as an alternative to the traditional CNN models, which showed significant improvement in performance in tasks such as image classification. The author focused on extracting building footprint areas from high-resolution (VHR) images(Song, Zhu, and Zhu 2023). Both these studies used deep learning methods for the segmentation of images. Training a deep learning model is usually challenging as it requires a large dataset with 3000 training samples used in this study. Moreover, training is computationally expensive, and the studies typically take 9-12 hours to complete.

Likewise, another study developed a machine learning-based image fusion network to detect buildings in an image. This model performed well in detecting irregular structures and buildings very close to each other. The author used three image fusion techniques to fuse Spot-5 and WorldView-2 images. The study also integrated height and textural information, which enhanced classification accuracy. The author utilized two image classification algorithms: Support vector machines and random forest, out of which the random forest algorithm gave better results (Taha and Ibrahim 2022). The high-resolution imagery of WorldView-2 and Spot-5 utilized in this study are, however, only accessible commercially and are expensive. In addition, the availability of such images could be a concern in specific locations due to security issues.

One of the other studies used light detection and ranging (LiDAR) derivatives data to classify buildings and extract building information, including height and footprint area. The study acquired the LiDAR data using an aerial platform and generated a point cloud to extract building footprints and heights (Kaplan et al. 2022). Although LiDAR can be a highly efficient technique for extracting building footprints, conducting a LiDAR survey is extremely expensive, making it infeasible for a larger study area (Wang et al. 2019). In addition, the desired outcomes of these classification strategies adopted in these studies are close to accurate real-time building footprints and usually involve a lot of computational costs and complexity in analysis. The end outputs from such extractions are not prominently used in energy simulations but for diverse purposes such as urban and transportation planning. On the other hand, urban or community-based energy simulations are usually performed to arrive at retrofit decisions that would minimize the energy consumption of the building stock, which may not require a fully error-proof building footprint dataset.

In addition to the non-availability of the building footprint datasets, another underpinning limitation is the diverse mix of buildings in the total building stock, each with a unique construction date, material, heating, ventilation, and air-conditioning (HVAC) strategy, and functional characteristics. For example, a study surveying 800 households in four climate zones of India revealed occupants' varied energy consumption patterns ranging between energy performance index (EPI) of 27-54 kWh/m2/year (Shukla et al. 2015). Because of this, a generalized strategy for energy retrofitting of India's existing building stock using modern energy codes, such as the energy conservation building code, may not be suitable for the full range of building households with various EPIs. On the other hand, depending on the kind of communities they live in, building characteristics and occupant behavior are becoming more similar (Ramalingam Rethnam and Thomas 2022, 2023a, 2023b). Reducing the scale of urban building energy models to building communities provides further flexibility in examining the building height information by observing the number of floors, as most of the residential buildings within a community follow a typical floor-to-floor height. For instance, a typical residential building in India follows the minimum room height given by the national building code, which is 3m (Bhattacharyya and Saha 2014). In addition, the non-geometric properties of the buildings within the community, such as the thermal conductivity of the building envelope, also comply with the regulations of the national building codes corresponding to the year of construction, which can be used for energy modeling (Ministry of Power 2017).

In the proposed study, the framework couples the most commonly accessible Google Earth satellite images for segregating the building footprints to building energy modeling. Google Earth is a geospatial application that visually gives users a holistic perspective of the Earth. Leveraging an extensive library of satellite photos and aerial photography, Google Earth allows consumers to explore nearly any location on Earth from their screens. (Hu et al. 2013). In this study, the images from Google Earth are segregated using computationally less intensive machine learning techniques such as minimum distance, spectral angle mapping, and k-means clustering with the community energy modeling schema for arriving at community-wide retrofit decisions. The proposed framework is also implemented in a case study building community in India, comparing the energy output of the model with the actual energy bills obtained from the government agencies for validation.

## Methodology

The various workflow stages for the framework are given in Figure 1 below.

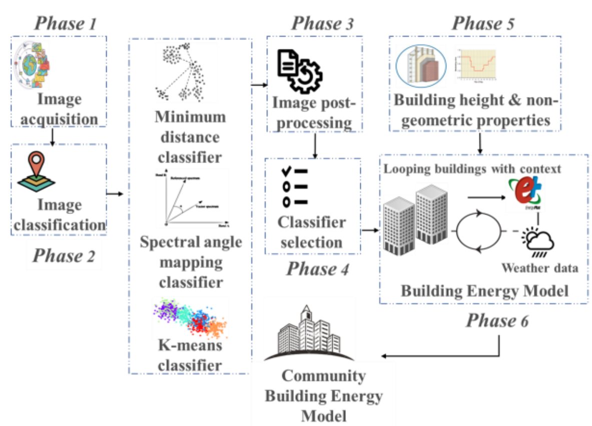


*Figure 1 Schematic representation of the framework*

In brief, the building footprint information, generally unavailable in a digital format, is extracted using machine learning techniques from the Google Earth image database and then coupled to community building energy modeling. Each stage of the workflow is explained in detail in the coming section, and a case study on a residential building community adopting the decision support system is also demonstrated.

**Phase-1: Image Acquisition**

The first stage of the framework is to extract the footprint areas of the buildings present within a community. A community is considered a collection of neighborhood structures comparable in their use, construction date, air conditioning schedule, and sharing facilities such as shared security systems, water storage, and parking space (Ramalingam Rethnam and Thomas 2023). The region of interest being relatively small compared to an urban scale, satellite images of very high spatial resolution are preferred for enhanced accuracy. This study uses the satellite data provided by Google Earth to extract relevant features of building footprints and tree cover, which are then exported to a spatial resolution of less than 1 meter, ensuring a high level of detail and clarity for subsequent analysis.

**Phase-2: Image Classification**

Extracting building footprints from the image requires categorizing trees and buildings separately. Quantum GIS (QGIS), open-source geospatial software, is used for performing unsupervised and supervised classification of remote sensing images using k-means, minimum distance, and spectral angle mapping classifier algorithms (Agus et al. 2018). In unsupervised classification workflow using k-means (Dalmaijer, Nord, and Astle 2022), the algorithm automatically identifies and groups pixels in an image without needing a labeled training dataset. The algorithm analyses the statistical properties and patterns present in the image to cluster similar pixels into distinct classes. The number of classes is specified as two to distinguish between the buildings and the tree cover, and the image is classified accordingly. The result obtained is later compared against those obtained through Supervised Classification techniques. The minimum distance and spectral angle mapping classifiers (Jawak et al. 2022) are employed for supervised classification for segregation. The study utilizes a Semi-Automatic Classification (SCP) interface within the QGIS platform to classify the image acquired from Google Earth by creating a training dataset. The training dataset plays a crucial role as it influences the accuracy and effectiveness of the classification results obtained. The training data is carefully selected to represent the classes of interest and cover a wide range of variations and characteristics present in the image data to ensure reliable classification outcomes. The quality of the training dataset is further validated by plotting spectral signature plots for different wavelengths. Any training data that was different in their spectral wavelength to a great extent is again carefully analyzed and refined to ensure the correctness of the dataset.

**Phase-3: Post-Processing**

The process of image classification results in a raster file having different classes marked as different colors. However, for further analysis of each class, the raster file is converted to a vector file and then split into separate files for a focused analysis of each class of buildings and trees. The distorted building polygons obtained due to the presence of dense tree cover are corrected manually to ensure closed building footprint curves.

**Phase-4: Classifier selection**

Since the building footprint area closely influences the energy use intensities of the building stock, the results extracted from the classifier algorithms are compared with the secondary dataset of existing building footprints already collected. The percent error (PE) is used to estimate the deviation between the building footprint areas obtained from the classifier algorithms and those collected from the secondary dataset, and the best-performing classifier, whose outputs are further considered for the community building energy modeling, is selected.

**Phase-5: Building height and non-geometric properties**

Assigning the building height information and the other non-geometric parameters to the building community is the next step. The building height information is collected from a site survey by considering the number of floors of each building within the community. The common non-geometric properties required for the study include the building construction materials, Window-to-Wall Ratio (WWR), occupancy schedule, lighting, and equipment density. For parameter definition, appropriate country-specific database guides or references are used. Thickness, thermal conductivity, density, specific heat capacity, roughness, thermal absorption percentage, solar absorption fraction, and visible light absorption fraction are a few of the inputs allocated for the building envelopes.

**Phase-6: Building energy modeling**

The creation of building energy models is the final phase. After all required input data has been obtained or computed, the energy model of every building in the stock is built using EnergyPlus, an open-source application developed by the US Department of Energy (DOE). The shoebox model is used as the form of calculation for the proposed framework. In a shoebox model, the building's façade is clustered into simple representative zones based on the building footprint, which is of the regular geometry throughout. This approach is used as the shoebox approach proves to be 200 times faster than the multi-zone model, with an observed marginal error of 15% RMSE against the actual energy meter reading (Monteiro et al. 2017). This significant reduction in simulation time makes this approach suitable for even bigger building communities. The multi-step model production process includes the creation of 3D models, the definition of thermal zones, the assignment of envelope attributes, and the assignment of non-geometric parameters to zones.

Additionally, buildings in the community are automatically looped along with the neighborhood shading context through scripting in the open-source Rhino-Grasshopper interface. The energy simulations of individual buildings are accumulated sequentially to fully develop the community building energy model ready for deployment with various energy-efficient retrofits complying with the Energy Conservation Building Code (ECBC) (Ministry of Power 2017). However, their accuracy and dependability must be thoroughly examined before employing the results of the building energy models to drive decisions in domains such as policy-making. The real-time annual energy consumption data of the building community gathered from the government agency is used to validate this study extensively.

## Simulation

The case study is based on a group of four separate apartment-type buildings that are part of an educational institution in Mumbai, India. Each of the apartment-type buildings has three floors with a total height of 10m. Step-by-step implementation of the methodology section is followed consecutively. Apart from the geometry information, the primary inputs include the roof material, wall material, glazing type, site orientation, window wall ratio, and the cooling set point, which are critical for investigating the energy consumption of a building or building stock (Albatayneh 2021). A description of the baseline building envelope materials from the site survey and a list of the materials' associated thermal transmittances derived from appropriate reference codes are given in Table 1. The modeling assumptions taken into account during the analysis of the building community with the pertinent reference codes used are listed in Table 2.

*Table 1 Building envelope baseline characteristics*

| **Building fabric** | **Baseline description** | **Baseline U value (W/m$^2$-K)** | **ECBC U value (W/m$^2$-K)** |
|---|---|---|---|
| Roof | 100 mm RCC + 50 mm foam concrete + waterproofing | 1.08 | 0.33 |
| External wall | 1.25 cm cement plaster + 22.5 cm brick + 1.25 cm cement plaster | 2.13 | 0.40 |
| External window | Single clear glass | 5.8 (SHGC 0.8) | 3 (SHGC 0.23) |

*Table 2 Modeling assumptions used in the community building energy modeling*

| | | |
|---|---|---|
| Occupancy-related | Occupant load factor: granularity - m$^2$/person<br>Occupant internal heat gain: granularity - hourly | (Shukla et al. 2015)<br>(ASHRAE 2017) |
| Air-conditioning | Air-conditioning schedule: granularity - hourly | (Rawan and Shukla 2014) |
| Infiltration | granularity - hourly | (ASHRAE 90.1 2013) |
| Lighting and Electrical equipment | granularity - hourly | (ASHRAE 90.1 2013) |

The image extracted from Google Earth before any processing where the four buildings that form a community are present is given in Figure 2.


*Figure 2 Building community as visible in the unprocessed Google Earth image*

The visual interface of the developed model for the simulation in the Rhino-Grasshopper interface, with EnergyPlus as the thermal engine, is given in Figure 3. The machine learning and energy simulation results obtained for the study are described in the following section.

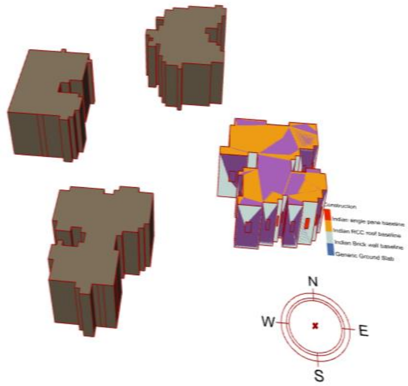


*Figure 3 Visual interface of the community building energy model*

## Discussion and Results

After the image acquisition, as explained in the methodology, the quality of the training dataset is significant for the image classification algorithms to work efficiently. This is ensured by plotting spectral signature plots for different wavelengths. Spectral signature measures the amount of electromagnetic radiation (EMR) reflected or emitted by an object at varying wavelengths. Different materials interact with different wavelengths of EMR and produce a spectral signature that is unique to the particular material. This unique property of spectral signature plots provides a good measure to judge the quality of training samples created. The result of the signature plots before and after refining the training dataset to make the values similar across all wavelengths is given in Figure 4, which is then used by classifiers.

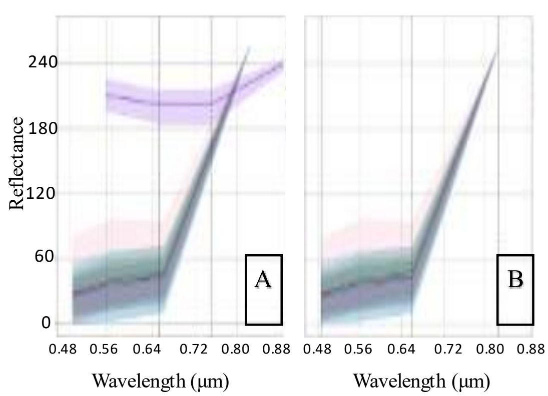


*Figure 4 A) Signature plot of training dataset before refining B) Signature plot of training dataset after refining*

Post signature plot results, the building footprint extraction results from the different classifier algorithms selected are given in Figure 5, and the overlaid classified image from the minimum distance classifier over the raw image is given in Figure 6.

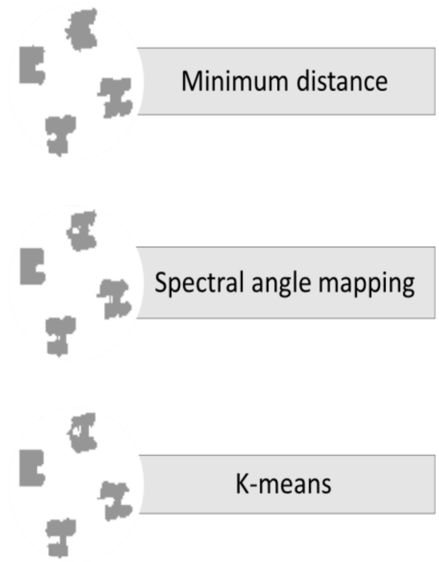


*Figure 5 Visual representation of the building footprint extraction results from different algorithms*

*Figure 6 Classification result of minimum distance algorithm overlaid on the Google Earth image*

Further to the building footprint extraction results, the mean PE is evaluated by comparing the footprint area outputs of the different classifiers with that of the secondary dataset, and the results are shown in Figure 7.

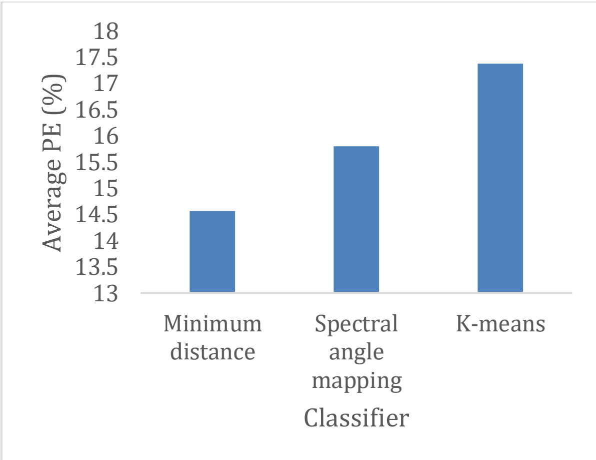


*Figure 7 Average building footprint PEs of classifiers with that of the secondary dataset*

The average PE for different algorithms is 14.62% for Min Distance, 15.79% for Spectral Angle Mapping, and 17.37% for Unsupervised Classification. The minimum distance classifier is observed to have a fairly close value with the secondary dataset, outperforming the other two and hence considered as the geospatial input file for the community building energy model. All the buildings within the community are looped automatically along with the neighborhood shading context, as given in Figure 8, and the energy simulations of individual buildings are accumulated consecutively to fully develop the community building energy model.

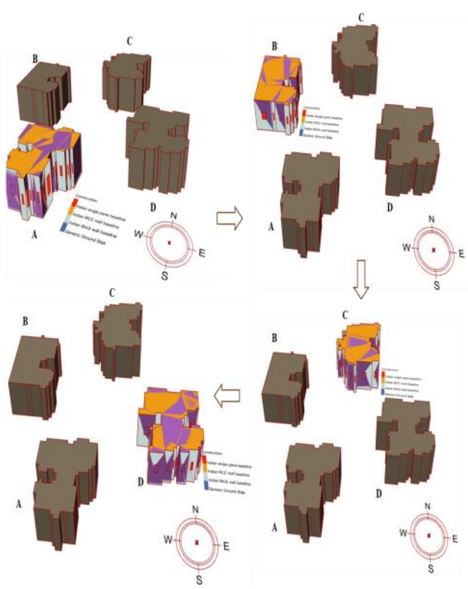

*Figure 8 Looping different buildings: from building A to building D, one building at a time, taking the remaining three buildings as shading contexts.*

The simulation results indicated that the annual energy consumption of the building community with baseline building envelope characteristics is 108.95 MWh, and the actual energy consumption is 107.21 MWh, as shown in Figure 9, with a PE of 1.62%.

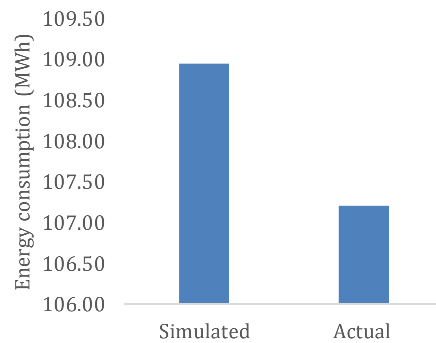


*Figure 9 Comparison between the annual simulated and actual energy consumption of the building community*

In addition to the overall energy consumption of the building community validated, the individual building's annual energy consumption was also evaluated against the actual energy consumption, and the results are given in Figure 10.

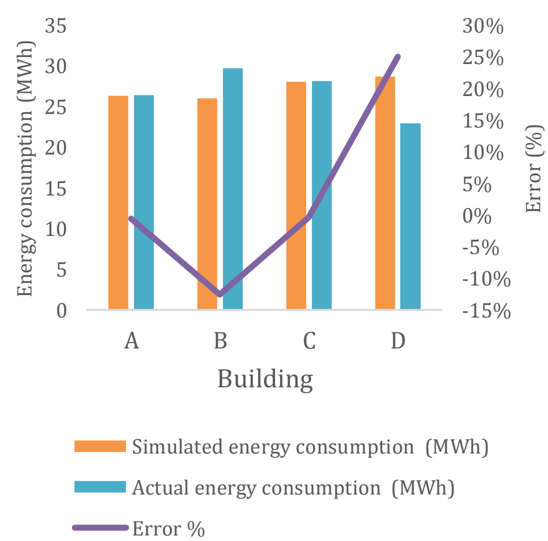


*Figure 10 Comparison between the simulated and actual annual energy consumption of individual buildings*

It was observed that three of the four building energy models gave a reasonably accurate energy consumption value, with the PE varying between the acceptable range of 1% - 15% (Cerezo Davila, Reinhart, and Bemis 2016), except for building D, with a PE of 25%. To check whether the error in the building footprint area from the classifier had the most significant impact on the results, the PE from the energy consumption was plotted against the PE in the footprint area and is given in Figure 11.

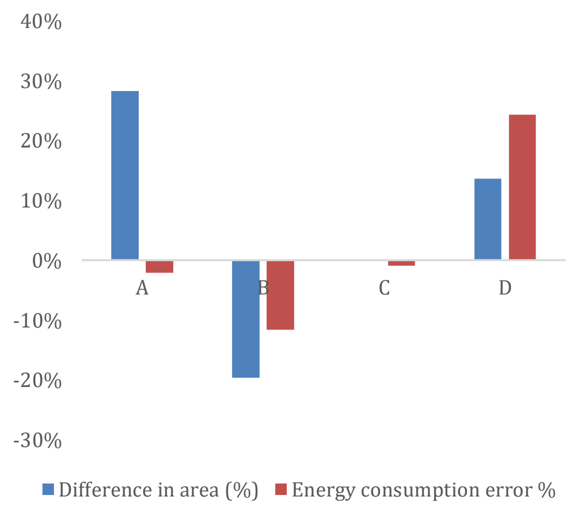


*Figure 11 Comparison between the PE of the building footprint area extracted from the classifier output and the PE of simulated energy consumption for individual buildings*

Although the building energy model of building C with the least building footprint area error exhibited the least PE in the simulated energy consumption, it is observed that the difference in building footprint area, standalone, could not explain the deviation. For instance, building A showed a PE of 21% in the building footprint area but only with a PE of 1% in energy consumption. The exact shape of the building, the shading effects of neighboring buildings, and the uncertainty in the energy modeling inputs, such as building envelope thermal conductivity and electrical and occupancy schedules, are found to be a few reasons for the observed deviation. In the energy-efficient scenario where the building envelopes that include wall and roof insulation, glazing, and solar heat gain coefficient (SHGC) are ECBC compliant, the annual energy consumption of the building community dropped to 108.57 MWh. The energy consumption spread of the baseline and energy-retrofitted building community is given in Figure 12.

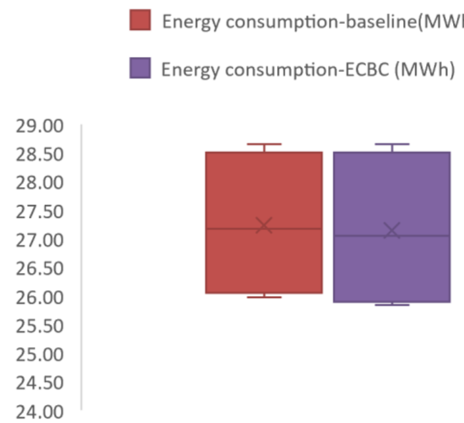


*Figure 12 Energy consumption spread of the baseline and energy-retrofitted building community*

The observed reduction in energy consumption by adopting ECBC measures is marginal, with only an observed drop of 0.34%. When investigating the reason for such a small drop, it was found that the entire building community had only an average of about 1.2% cooling space, accounting for the energy consumption of 1.27 MWh.

In contrast to developed nations, most developing nations lack fully air-conditioned spaces. Estimating the actual cooling space of the building stock is critical for determining accurate energy consumption in community building and creating custom set points and schedules. This study estimated the number of AC outdoor units fixed at each community building using a simple site inspection procedure. The carpet area of the bedrooms, which are the only rooms in a typical housing unit with air conditioning, was then measured and used to determine the building's cooling space. This information was obtained from government agencies or through surveys. However, any inaccurate estimating of this cooling space can alter the selection of the right retrofit strategies for the entire building community. To summarise, the conclusion that using a retrofit strategy does not seem to offer a significant amount of energy (or) financial advantage with only a 1.2% cooling space fraction, as well as the critical implication that the benefits of ECBC compliance should not be ignored when considering only the current building stock context, should be taken into consideration. It is vital to consider the possibility of adding cooling space and any potential severe future weather conditions to guarantee the code's efficacy.

The case study's validation and evaluation of the potential for various retrofits to reduce energy use intensity by putting the framework into practice support the study's main idea, which is to implement frameworks of this kind in developing nations to envision rapid decision-making for mass retrofitting using a decentralized approach of building communities, even when the building footprint dataset is unavailable readily. With a few minor adjustments to the inputs, which include Google Earth images, building envelope thermal transmittance, and cooling space fractions, policymakers can immediately put into practice the developed framework for swiftly evaluating building retrofit projects. The framework is not case-centric and can be applied to any country where sufficient building footprint datasets are scarce to arrive at probable energy reduction estimates possible by employing various retrofit options.

## Conclusion

This study presented a holistic customizable framework for developing close to accurate community-building energy models, even when the building footprint information is not available digitally, by extracting them from simple Google Earth images using machine learning techniques. After accounting for regional relevance, this study offered a way to use the developed and validated community building energy model to understand how energy conservation compliance affects the energy consumption of the stock of residential buildings. The energy use consumption of the case study building community is found to be 108.95 MWh, with a very low percent error of 1.3% when validated by the actual energy consumption readings. Further, the energy consumption drops to 108.57 MWh when the building envelopes comply with the energy conservation building code. The findings also showed that the cooling space fraction significantly affects the energy-efficient building envelopes' capacity to reduce energy use. Therefore, any error in the cooling load analysis could result in costly retrofit procedures. The implications of this research are far-reaching, especially in building automation, combining remote sensing, GIS, and machine learning to extract building footprints with energy analysis to accelerate the decision-making process of engineers and architects. It enhances the ability to design energy-efficient buildings at an urban/community level and contributes to the global net-zero goal.

Although the framework can extract the building footprint information from satellite imagery, the building height is collected from a site survey, which is a limitation. As explained in the background, although the limited scope of considering only a building community makes this possible with the least inaccuracy, future studies can delve into methods of extracting the building height information through automated geospatial coupled photogrammetry techniques.

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