Estimating Cooling Energy Demand from Building Attributes and Environmental Parameters using 3D City Models

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Abstract

Most of the global population have shifted to urbanization with advancements in technology. With this transition comes the responsibility of applying these technologies to promote sustainable development practice. Since energy demand is highest in the urbanized areas, it is important that proper assessment and management of energy resource is considered in policy-making and urban planning. This study investigated the estimation of cooling energy demand in Iloilo City Proper, Philippines using a 3D city model integrated with building attributes including building functions and year of construction, while also taking into consideration meteorological factors in the area. The proposed method used the application SimStadt2.0, following the German computation standard DINV18599. Building functions and year of construction were extracted from available building attributes data and satellite images respectively, using the free and open-source software QGIS. A CityGML Level of Detail 1 was generated from 3Dfier using building footprints and LiDAR point cloud data, along with the extracted building attributes of the 5,426 buildings. Meteorological data from INSEL 8 were also considered in the estimation of cooling energy demand in SimStadt2.0. Results showed a monthly energy demand of 12.33 kWh to 313,530.08 kWh in the study area. The estimated energy demand values were higher than the standard mean for different building functions in the country, but within the expected range of values for each season. Urban Heat Islands (UHIs), analyzed using Land Surface Temperature (LST) values, also have significant correlation to areas with higher cooling energy demands. However, inconsistencies can imply the need for further investigation.

1. Introduction

1.1 Background of the Study

Sustainability practices integrated in the urban way of living are becoming increasingly significant as urbanization continues to grow. These include applications of digital technologies combined with simulations of real-world processes. With this, both the urbanization and its effects expand the demand for energy consumption, and proper estimation and management of this resource becomes significant for said sustainability practices in urbanized areas.

The United Nations projects that more than half of the world’s population would be living in urban areas by the year 2030 (United Nations Statistics Division, 2019). As such, leading issues brought about by urbanization include pressing environmental concerns of energy, efficiency, and sustainability. In terms of energy, urban areas are responsible for 75% of the global primary energy consumption, and would continue to rise with the continuous urban growth (Chowdhury et al., 2019). Studies on sustainable use of resources provide important insights that can be used for policy-making. Thus, it is necessary to have a systematic approach in estimating the energy consumption or demand of buildings for more efficient and sustainable use.

3D city models have been getting a bigger role in applications of sustainable development as more tools are developed to create them. Providing for efficient representation, visualization, and management of large amounts of data, 3D city models offer limitless opportunities to be further studied under different applications. It can be created and refined using free and open-source software, as well as be shared and replicated by different researchers due to its interoperability. Issues of sustainability can then be tackled across cities, with executable simulations and data management all within the 3D city models– greatly opening possibilities for smarter cities.

Urban population necessitates energy to power up the cities, thus managing and regulating this resource becomes crucial in the move towards sustainable development. A closer look on estimating energy demand would tackle different factors, namely, the physical foundation of buildings, environmental aspects, and other human-induced functions. This study estimated the cooling energy demand in buildings by using 3D city models with building attributes and weather data particular to the study area to determine if these are critical parameters needed to be considered in the context of the country.

1.2 Significance of the Problem

According to the Compendium of Philippine Energy Statistics and Information (CESI), energy data submitted to the Department of Energy (DOE) are reported by different energy stakeholders such as oil companies, power generating companies, transmission, and distribution utilities etc. Supplemental data such as the Household Energy Consumption Survey (HECS) are also gathered by the DOE. The data are then compiled and used to generate the Energy Balance Table (EBT), which is a presentation of basic supply and demand data for all fuels, which is used mainly for policy making.

This study aims to develop an alternative approach to acquiring data for cooling energy demand by using 3D city modelling with weather data to improve the methodology for accounting energy demand. Currently, the only sources for such data are the petroleum and electricity sales report of companies. The Philippine Statistics Authority (PSA) in coordination with the Department of Energy (DOE) conducts the HECS as a series of surveys to gather data on household energy consumption. According to the PSA website, HECS was supposed to be conducted every 5 years, but the latest one was released in 2011, which is already over 10 years ago. Considering all of these, as it stands, there is a clear lack of updated and supplemental data for energy demand.

The objective of the study is to estimate the cooling energy demand in buildings in Iloilo City Proper, Iloilo using 3D city models with building attributes and weather parameters. The cooling energy demand estimation considers the buildings attributes of building function and year of construction, as well as the environmental parameters of global horizontal irradiance and ambient temperature. The success of this study can potentially lead to more investigations using wider sets of data and parameters specific to the country, in hopes of contributing greatly to the countries' capacity to build smarter cities.

The novelty of this study is the integration of cooling energy demand estimation to the generated 3D city model of Iloilo City Proper. The study makes use of already existing free and open-source software to create the models, to integrate semantic information, and to then estimate the cooling energy demand from available datasets. The study combines all these methods to design a workflow with an efficient and accurate product.

2. Objectives

The study aims to create an estimation of the cooling energy demand using building attributes and environmental factors in the study area located in Iloilo City Proper of the Iloilo Province, Philippines. Specifically, the objectives of this study are:

1. To extract building functions and building year of construction from available data,
2. To generate a CityGML Level of Detail 1 (LOD1) 3D city model of the study area,
3. To integrate extracted building attributes into generated 3D city model,
4. To estimate cooling energy demand in the study area.

3. Methodology

The cooling energy demand in the city is to be estimated from generated 3D city models with attributes such as building year of construction, and building function. The information integrated in the estimation provides depth in the estimation of cooling energy demand–as more variables are added compared to considering just the geometry of the buildings. The generated city model produced a rich storage of information that can also be used for various other applications.

The general workflow, is divided into parts consisting of (1) data pre-processing, (2) 3D model generation, and (3) cooling energy demand estimation. The (4) verification part is added to compare resulting values to existing methodologies computing for energy.

Fig. 1 presents the detailed flowchart for generating the LOD1 city model, while Fig. 2 presents the flowchart for the calculation of the cooling energy demand in buildings using SimStadt 2.0.

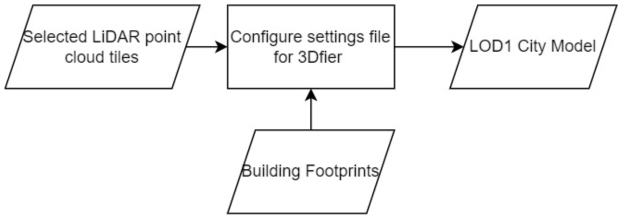

Figure 1. Workflow for generating LOD1 city model.

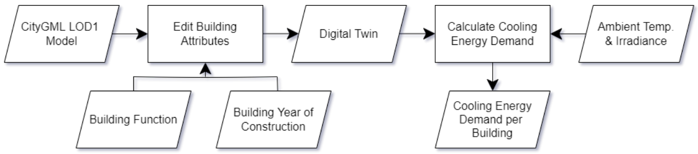

Figure 2. Workflow for estimating cooling energy demand.

The selected LiDAR point cloud tiles are determined by visually checking which tiles cover the area of interest. Together with the building footprints, these data are placed in a single folder. After which, the input and output options are defined in a settings file with YAML format. This file tells the 3Dfier where to find the input files, what type of lifting process to do, and the output file format of the LOD1 model. 3Dfier then generates the LOD1 model according to the settings file.

After generating the LOD1 model, the building attributes are checked using FME Workbench. This step is necessary to check if all the buildings have the proper values for each attribute, especially Building Function and YOC. If there are buildings with missing or incorrect values, it is corrected accordingly using Workbench. The output is then imported into Simstadt for the calculation of the cooling energy demand. Simstadt internally validates the geometry of the buildings, as a result some of the buildings are disregarded and no calculations were performed for those buildings. The ambient temperature and irradiance values are automatically acquired by the software from the built-in INSEL database.

3.1 Data and Pre-processing

Data	Source
Building Footprint	Project LUNGSOD; Iloilo Local Government Unit
LiDAR cloud point data	UP DREAM
Building year of construction	Derived from satellite images of Iloilo City taken from 1990, 2000, and 2010
Building function	Derived from Iloilo Local Government Unit Comprehensive Land Use Plan, and Points of Interest from Project LUNGSOD

Table 1. List of data used and corresponding sources.

One way of generating an LOD1 3D city model, according to Ledoux et al., needed the inputs for the building footprints and the point cloud data (2021). Following this, the researchers requested for already available data to avoid the high expenses and impracticality of first-hand data gathering. Available data of the LiDAR point cloud was requested from the University of the Philippines Disaster Risk and Exposure Assessment for Mitigation (UP DREAM) Program, and building footprints were made available by the Project Link-Up of Geomatics and Social

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Science Research for the Development of Smart Cities (LUNGSOD) for Iloilo City.

The building information acts as an important part of both generating the 3D city models and calculating cooling energy demand. The building year of construction and the building function are considered as the minimum required physical information for the energy simulation program, as they consider the element of time and use of the building. Building function refers to the usage of the building according to the comprehensive land use plans or zoning, such as the residential, commercial, and industrial areas. Aside from these classifications, some unique building functions can also be specified, such as the use for educational facilities, medical facilities, entertainment, etc.

Additional information such as the building materials used also provide a more detailed city model, as well as other useful information regarding the buildings to be integrated into the attributes. Heat transfer coefficients and indoor air temperature would also be useful for a more accurate calculation of the cooling energy demand. These can be used depending on the availability of data.

The environmental parameters used for the cooling energy demand estimation are temperature in the sky and on the ground, and the irradiance levels which can be classified between Direct, Global, and Diffuse. These are already available and can be accessed through the different sources used by the software SimStadt 2.0. The available databases are INSEL 8 for offline use, and PVGIS for online use. It also allows users to upload a Typical Meteorological Year file (TMY3), given that it follows the correct template accordingly.

3.1.1. Extracting study area

Given the chosen study area that is the Iloilo City Proper in Iloilo City, the LiDAR point cloud data had to be pre-processed to reflect the area from all of the available data spanning the entire city. As shown on Fig. 3., a total of four (4) tiles were selected to represent the Iloilo City Proper–neatly arranged in a rectangular shape side by side. QGIS was used to visualize the LiDAR point cloud data, and the specific LiDAR tiles were determined by locating the study area from the overlaid OSM basemap.

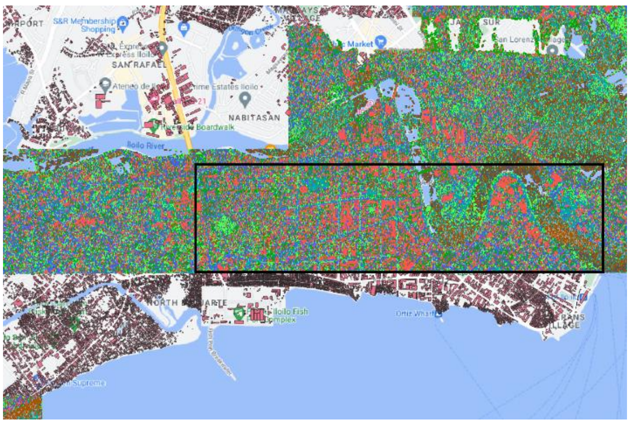

Figure 3. The LiDAR point cloud data with the study area outlined in black.

3.1.2. Classifying building footprints

The classification of building functions was based on the Iloilo City's Comprehensive Land Use Plan (CLUP) of 2021 to 2029, as shown on Fig. 4. The plan consists of zoning the district to land uses such as the commonly residential, commercial, industrial zones, as well as the institutional, parks and recreational areas, and transport and utility zone. Non-built up areas can also be seen in the plan, listed as agricultural, mangrove forest, water, and landfill zones. Specific points of interest (POI) are also noted to specify unique buildings such as schools, heritage houses, greenhouses, and others.

The building functions are integrated into the 3D city model to be reflected and considered in the estimation of cooling energy demand. The application FME Workbench is used to edit in the functions depending on the classification results.

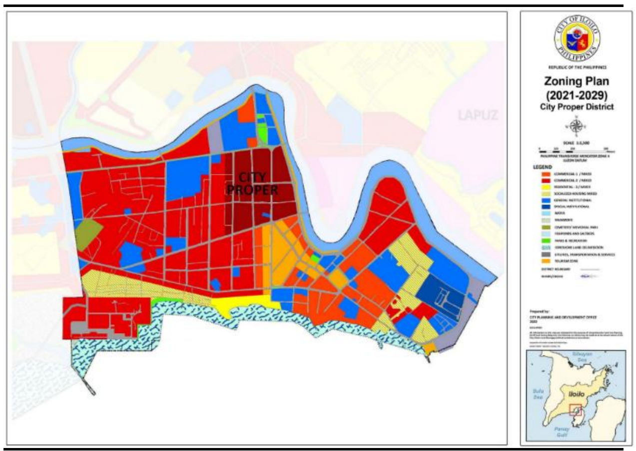

Figure 4. Comprehensive Land Use Plan of Iloilo City Proper 2021-2029.

3.1.3. Categorizing building year of construction

As there is currently no available data for the building years of construction in the city, the age ranges of the built-up areas can alternatively be considered. Satellite images from Landsat 4-5 TM of the Iloilo City Proper spanning time periods of the 1990, 2000, and 2010 are used to investigate the built-up in the area. By overlaying the extracted Normalized Difference Built-Up Index (NDBI) values from the satellite images to the building footprints using QGIS, construction year of the buildings can be determined. NDBI is commonly used for the extraction of built-up areas, following a formula:

$$NDBI = \frac{MIR - NIR}{MIR + NIR} \tag{1}$$

where MIR is middle infrared and NIR is near infrared, which produces a range of values from -1 to +1 with +1 being the most built-up (Zha et. al., 2003). NDBI was found to be a commonly used tool for land use/land cover applications as built-up areas have relatively higher reflectance in the MIR wavelength range than in the NIR (Malik et. al., 2019). Limitations of the NDBI process include the assumption that positive values are built-up without discriminating from barren and bare land (Zha et. al., 2003). For our study, pixels with values with greater than 0 are considered built-up areas.

The years 1990, 2000, and 2010 were assumed to be where most of the buildings are constructed to further simplify the process of categorization. The year ranges are also used rather than assuming a uniform year of construction for all the buildings, to consider significant developments in the city since the 1990s.

3.2 Generating 3D City Models

The LOD1 3D city model of Iloilo City was created using the 3Dfier application. 3Dfier takes in 2D polygons such as building footprints, and lifts them to become 3D from the elevation that comes from the point cloud data. 3Dfier takes the average height of all the points within a footprint, and lifts it to that height. Every polygon is triangulated and the lifted polygons are "stitched" together so that one digital surface model (DSM) is constructed (Ledoux et al., 2021). 3Dfier allows outputs in CityGML with attributes ID and height. This is the file format supported by the energy simulation software the researchers are planning to use.

The researchers were able to successfully generate a LOD1 3D City Model using 3Dfier. The inputs are 1) selected LiDAR point cloud tiles covering the Iloilo City Proper and 2) Building Footprints. A configuration file in a YML file format is required to specify input and output options. This configuration file defines the input datasets, lifting options, and other options desired by the user. The researchers used the extent option to filter the area to be 3dfied from the input building footprints.

3.3 Estimating Cooling Energy Demand

The estimation of cooling energy demand was conducted using the urban energy simulation software SimStadt. SimStadt, developed by HFT Stuttgart, accepts CityGML as input and allows to perform different analyses on buildings, such as the computation of the cooling energy-demand of buildings based on the energy-balance method. The method follows the German standard DIN V 18599 which defines the algorithms and formulas needed to calculate energy demand in buildings like heating and cooling. The energy balance includes all heat sources (intern gains, solar gains) and sinks (transmission, ventilation) within the building zone; its results are the monthly space heating and cooling demand (University of Applied Sciences Stuttgart, n.d.).

SimStadt 2.0. requires the buildings to have at least attributes for years of construction and building function. With these attributes, users can connect to its libraries for augmenting information on the input model. These libraries are the Usage library and Building physics library. The building function attributes are mapped to different usage types (i.e. residential, office, education, health care, etc.). This allows users to access the usage library for each building. The library gives access to parameters that can used for energy analysis. The parameters are grouped into parameter topics such as space cooling, space heating, ventilation etc. For space cooling, the parameters are “set point/set back temperature” and “cooling schedule per day.”

In addition, the building physics library includes the parameters related to the thermal characteristics of materials of the building. A geometric preprocessor of the software classifies each building into different building types. These building types have predefined parameters according to year of construction, while a weather processor is also included in the calculation of the cooling energy demand. The software allows access to external software INSEL 8, which is a database for local outside temperature.

4. Results and Discussion

4.1 3D City Model Generation

The 3D city model generated included all the characteristics and attributes necessary for the cooling energy demand estimation. Thus, aside from the generation of the models, the results of identifying building functions and building year of construction are also detailed below.

4.1.1 CityGML Level of Detail 1: The study area covered a total of 5426 buildings with varying shapes and sizes. Shown below are the generated 3D city models of the study area, using the CityGML LOD1 as in Figure 5.

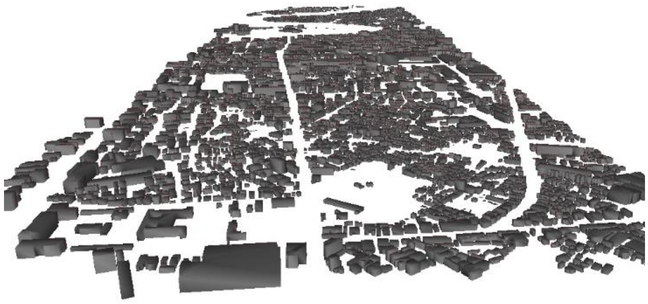

Figure 5. LOD1 3D city model generated using 3Dfier.

Upon inspection, it was found that most of the buildings were properly lifted except for a few floating buildings. These buildings were not removed by the researchers, as the estimation software automatically validates the geometry of the City Model and excludes such features that do not pass the geometry check.

An LOD1 3D city model was found to be more accessible to use than more accurate LODs due to its basic geometry that can be generated from already existing data. According to Malhotra et. al., differences in results of LOD1 compared to reference LOD2 models were only due to the less precise geometry, as the former would not have the roof types that can be found on the latter. Generating an LOD2 model might produce higher accuracy, but a basic LOD1 model can already be enough for the building geometry to be investigated as its volume in this study (Bijecki et. al., 2016; Dukai et. al., 2019).

4.1.2 Building Functions: Classifying buildings into their functions greatly depended on the available data. The building footprints from the Iloilo City Local Government Unit had already designated building types as seen in their ground data taken from Project LUNGSOD. Comparing these to the city’s Comprehensive Land Use Plan (CLUP) for the years 2021-2029, it can be noted that most of the buildings in the study area are still residential, despite the planned use for commercial zones. Residential buildings took up most of the smaller sized buildings, while larger sized buildings were either for education, commercial use, office and administrative, or mixed use. Other than these observations, the types matched the CLUP zoning, with little to no variation, as cross-checked with unique buildings manually.

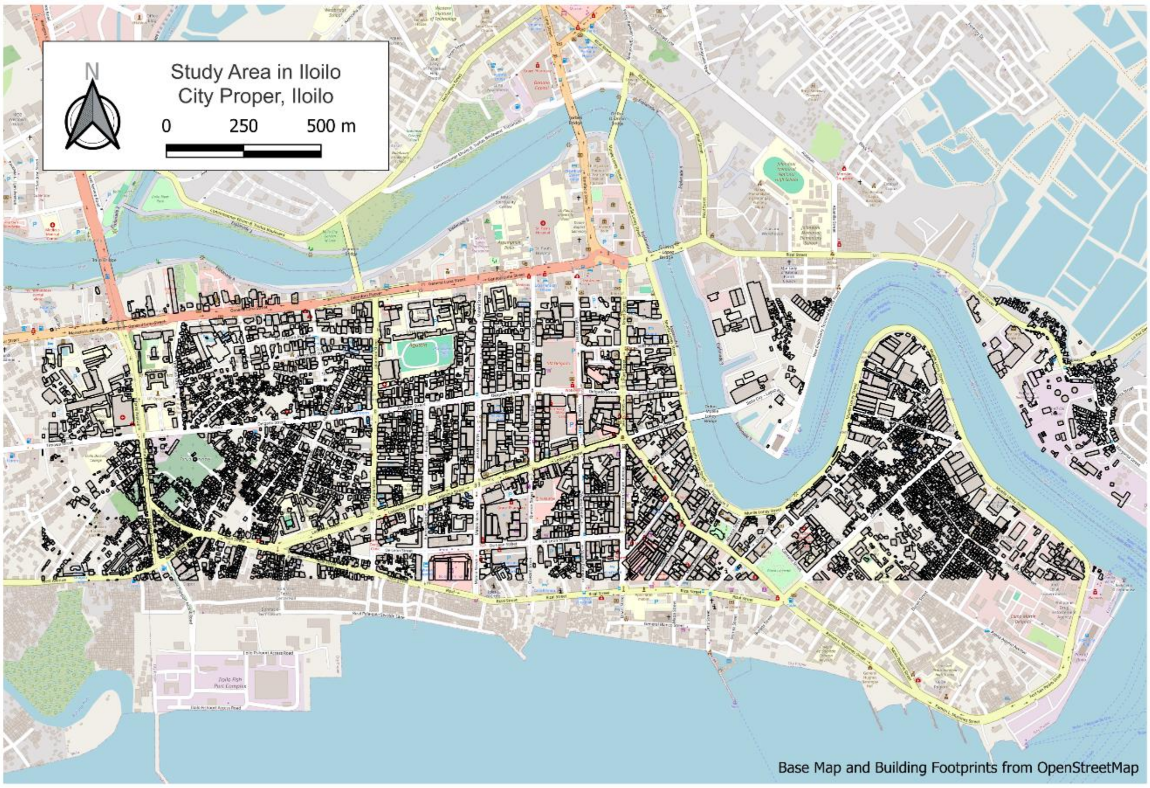

Figure 6. Study area in Iloilo City Proper, Iloilo City.

The building types were then reclassified to building functions within the range available in the cooling energy demand estimation software using QGIS. The range of classifications in the estimation software primarily focused on how the building uses cooling/heating energy, and thus the following simplifications were used: churches and places of worship categorized as event location; stay-ins, lodges, and hotels were categorized as hotels; private companies such as those with business-to-business models and banks, and government buildings categorized as office and administrative; commercial buildings and mixed use with commercial use categorized as retail; factories and warehouses categorized as industrial; and gas stations, cemeteries, and public heritage sites as non-heated.

The classifications followed a legend that was integrated into its attributes, and is shown below as Table 2.

Education	3023
Event Location	3036
Hall	3038
Healthcare	3051
Hotel	3075
Industry	2112
Non-heated building	3074
Office and administration	3012
Residential	1010
Restaurant	2081
Retail	2050
Sports Location	3211

Table 2. Building Function Classification Tally.

4.1.3 Building Year of Construction: Since there was no available data for the building year of construction of buildings in the study area, the Normalized Difference Built-Up Index (NDBI) was used to process Landsat satellite images taken from three different periods: 1990, 2000, and 2010. NDBI allows for higher accuracy identification of the built-up areas using QGIS (Karanam, 2018), and defines urban built-up areas as “impervious surfaces or man-made coverings and constructions,” (Liu et. al, 2018). The identified built-up areas existing on the respective satellite images were noted in the year of construction attribute, with newer buildings recorded per satellite image. Results of the NDBI processing are shown in Fig. 7.

4.2 Cooling Energy Demand Estimation

The cooling energy demand estimation process started with integrating all the pre-processed variables into the generated LOD1 city model. This was then processed in Simstadt 2.0 to automatically calculate the cooling energy demand.

SimStadt 2.0 takes the CityGML input– the generated LOD1 model, to create an internal SimStadt model with placeholders for the imported model’s attributes. Then, the program proceeds with the pre-processing of the geometry, physics, and usage values. The geometry of the whole model is then checked and validated, along with the calculation of the volume and height of the buildings to constitute for the Geometry Preprocessor. The Physics preprocessor determines the building type and assigns properties that includes the U-value, storey height, infiltration rate etc., depending on the year of construction of the building. The Usage Preprocessor then assigns the building functions as integrated in the imported model. After

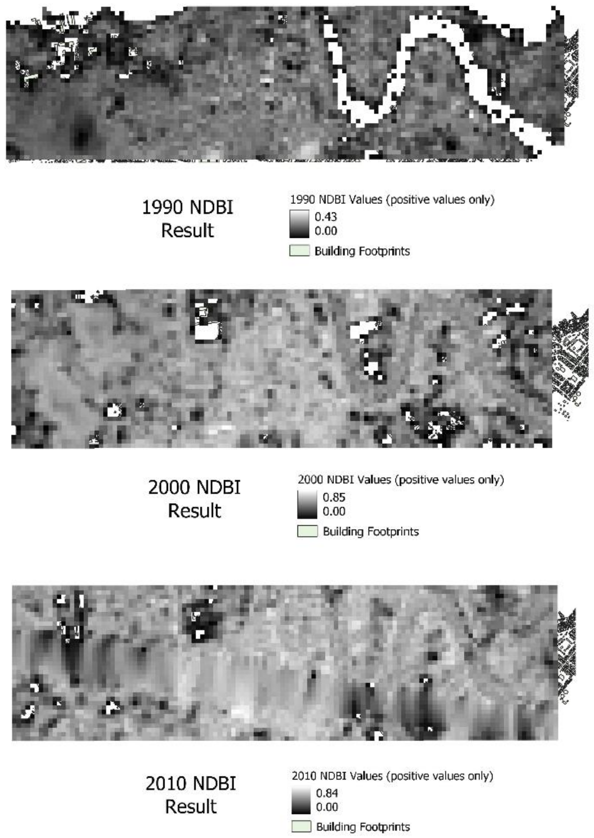

Figure 7. NDBI Results on the study area (a) for year 1990, (b) for year 2000, and (c) for year 2010.

preprocessing, the Weather Processor and Irradiance Processor retrieves weather data and irradiance data respectively from the location of the model either through manual importing of data or selecting from available databases in SimStadt 2.0.

Using the input CityGML LOD1 model with integrated building functions and building year of construction, and the weather and irradiance database of the Insel 8 software, the computed monthly cooling energy demand of the study area showed a range of 12.33 kWh for a non-heated structure and up to 313,530.08 kWh for a retail dedicated structure. The average monthly cooling energy demand processed according to each building can be seen in Fig. 8.

4.2.1 Effect of building functions: It can be noted that most of the buildings returned relatively lower values, and most of these buildings were classified under residential use. Multiple buildings classified with retail, education, and office and administrative were the ones that had notable higher values of cooling energy demand, most probably due to the predetermined higher occupancy rates and use of electricity. Expectedly, non-heated buildings returned the lowest values for cooling energy demand, followed by most of the residential buildings.

The Department of Energy Guidelines on Energy Conserving of Buildings provided an Energy Utilization Index, outlining the annual average energy consumption based on their building function, as surveyed by the International Finance Corporation (2020). These values can be seen below as Table 3. along with the computed results from this study. It can be noted that not all building functions have recorded averages based on the standard.

Building Function	Standard (kWh)	Computed (kWh)
Education	131	358.87
Healthcare	338	349.97
Hotel	174	157.10
Office and Administration	345	259.00
Residential	65	275.57
Retail	336	259.66

Table 3. Average annual energy consumption, standard v. computed results.

Overall, the estimated cooling energy demand for each building function produced somewhat realistic values when compared to standard average values. Some were even lower than the given standard: hotels, office and administration, and retail buildings. In contrast, significantly higher computed values were recorded for the education and residential buildings. The computed value for the healthcare buildings were higher but still somewhat close to the standard value.

It can be noted that the standards listed above are for the general energy consumption, while the computed values were only for the cooling energy demand of the buildings. These standards were used as there was no available data for just cooling energy consumption. Given this, the computed values should have significantly lower results as it is simply for cooling energy demand, and not for other uses of energy such as for lightning, entertainment, etc. The researchers assume that these values can be significantly improved with more accurate input data.

The accuracy of data used as values in the estimation of cooling energy demand can also be considered an indicator of how accurate the expected results can be. For example, building functions or primary usage of the buildings were only assigned based on the availability of data and the Iloilo CLUP. More accurate data and more detailed information such as occupancy and number of households would improve the resulting values.

4.2.2 Effect of year of construction: The year of construction of each building matters also in the calculation of cooling demand. It defines the U-value [W/m2K] of each building. The U-value is a measure of the heat transmission through a structure and it implies how well insulated the building is. The lower the U-value, the better the building retains heat. Most buildings have high U-values which is expected since most of the buildings have a year of construction of 1990 implying that the buildings are old and are not well insulated. Upon checking the results of the calculation, the building with the largest cooling energy demand per month has a mean U-value of 0.63 with a Retail function and YOC of 1990. Considering the mean U-Value of the building, 0.63 is low but still higher than the average mean U-value of all the buildings which is 0.6. The researchers can infer that the high cooling energy demand of the building is mainly due to its area and function. However, this portion of the research needs further study and targeted methodology to confirm.

4.2.3 Monthly and Seasonal Cooling Energy Demand: As the Philippines is considered a tropical country where there are only two seasons, it is also important to analyse the monthly and seasonal cooling energy demand in the buildings. According to the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA), the dry season consists of the months from December to May, while the wet season consists

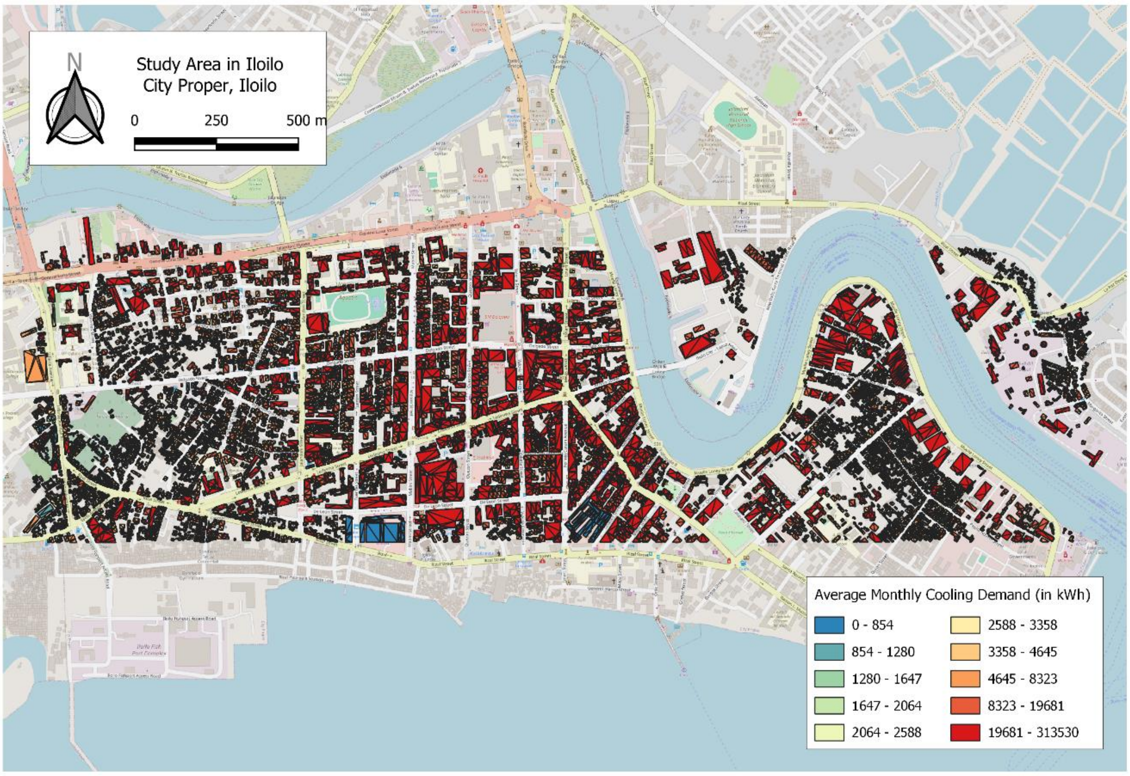

Figure 8. Average Monthly Cooling Energy Demand (in kWh) in the Study Area.

of the months from December to May, while the wet season consists of the months from June to November (2022).

Upon comparison with the results, the cooling energy demand for the wet season with months of June to November unexpectedly gave a higher value compared to the dry season with months of December to May. Initially, this was unexpected, as the wet season usually brings rainier weather and typhoons in the country, resulting in generally lower temperatures. However, looking into the further subdivision for the dry season, the highest cooling energy demand still comes from the Hot Dry Season with the summer months of March to May, and the lowest comes from the Cool Dry Season with months of December to February. These results are still validated by mean temperature per month, as recorded by PAGASA, with the coldest month as January while the hottest month as May (2022).

4.2.4 Comparing to Urban Heat Islands: For further analysis, resulting values of the cooling demand estimation are compared with the results of the Land Surface Temperature (LST) for both daytime and nighttime as observed in the study area. The methodology to produce the LST, as well as the engine used, were taken from the Project GuHEAT or the Geospatial Assessment and Modelling of Urban Heat Islands in Philippine Cities aimed to investigate effects of urban heat islands in the country (2020).

As more urban areas are developed, observed air and surface temperature significantly increase compared to areas with more rural environments, and these are called Urban Heat Islands or UHIs (Tiangco et. al., 2008). Project GuHEAT identifies the factors such as the amount of vegetation, building materials, urban design and geometry, and other anthropogenic factors as causes of UHIs (2020), with such factors tackling similar variables as with this study. The analysis of UHIs in the study area can provide a rationale as to possible reasons to explain results from the cooling energy demand estimation.

It can be noted that the computed LST ranged from 24.75 °C to 34.61 °C, a mean of 31.60 °C during the day, with notably cooler temperatures on the river and riverside, and hotter areas on the built-up areas. In direct contrast, the computed nighttime LST ranged from 21.00 °C to 22.49 °C, a mean of 21.74 °C with notably hotter temperatures on the river and riverside, while cooler on the built-up areas.

A significant part of the study area comprises a part of the Iloilo River, that then provides a comparatively lower temperature in the daytime and higher temperature at nighttime. Upon investigation on the Urban Cooling Island (UCI) effect of the water spaces in Iloilo City, Cruz et. al. found that water spaces do provide a cooling effect but only to an extent, and that the effect is dependent on the distance of the built-up areas from the water body (2019). Spatial and temporal effects of UCIs are also independent of each other– as sizes of the water bodies have little to no effect on UCI, and as the climatological factors can affect its temporal variation (Cruz et. al., 2019).

Comparing the results of the cooling energy demand estimation, the LST validates that areas in need of cooling are situated where most buildings are larger and dense. As Project GuHEAT states the direct proportionality between built-up areas and UHIs (2020), it confirms the higher demand for cooling energy in those areas. Malik et. al.’s investigations on LST and NDBI results also show the direct positive relationship between the two (2019).

Isolating the higher LST values with 33 °C to the maximum value 34.61 °C, it can be noted that these urban heat islands are well within the buildings requiring the higher values of estimated cooling energy. Most of the buildings within these islands are classified as retail, education, office and administrative, with a mix of the residential buildings, showing the effect of building function on the UHIs. This reinforces the assumption that cooling energy demand is also reflective of the existing UHIs in a specific area, although still inconclusive as further study still needs to be done.

5. Conclusion

The study was able to estimate the cooling energy demand in Iloilo City Proper through the 3D city model. A CityGML LOD1 3D city model was generated from LiDAR point cloud data and building footprints and integrated with classified building functions and extracted years of construction from NDBI results. The study showed that the feasibility of the LOD1 3D city model for energy demand estimation was due to its accessibility and availability of data for easier generation. Buildings used for retail and commercial, office and administrative, industrial, and educational functions yielded higher values of cooling energy demand. Moreover, older years of construction and type of materials also contribute to higher values of cooling energy demand.
The estimated cooling energy demand was found to be within reasonable values in the Philippine context. Upon comparison with the LST values, the estimated cooling energy demand also correlate well with the Urban Heat Islands in the city. Key factors in accurately estimating cooling energy demand include the building's function, the year of construction, and the ambient temperature and solar irradiance. This study demonstrated the potential of using digital twins to estimate energy demand in the Philippines, paving the way for more sustainable and smarter cities in the country.

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