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Virtual Singapore integration with energy simulation and canopy modelling for climate assessment

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Abstract. Urban heat island (UHI) can be described as characteristics of warmth for both the atmospheres and surfaces in cities compared to rural surroundings. The attention on UHI has helped to advance the development of urban cooling strategies in Singapore. However, these strategies are often implemented at different levels with different mechanisms, and studies on the environmental implications of these strategies are often segregated. Therefore, understanding on how the urban canopy works is vital to analyse the energy performance, because canopy modelling is significant in estimating urban weather conditions, which affects the heat gain intake for buildings. It is thus become imperative to develop an integrated model for accurate prediction of weather conditions at different scales. By utilizing the Virtual Singapore (VSg) database, this study explores the development an integrated simulation platform, named BESCAM, for climate assessment and district energy demand. It focuses on urban canopy modelling and building energy simulation. The approach is to use CityGML from VSg as input, which comprises converted Building Information Modelling (BIM) buildings. Then, an urban canopy modelling (UCM) is developed to assess the microclimate condition with urban morphology consideration. Afterwards, building energy simulation can be conducted consecutively using EnergyPlus by integrating microclimate and building information. Hence, the BESCAM platform would offer a unique opportunity to architects, engineers, and scientists to use the same source of information, using VSg database, for conducting their own analysis and compare their conclusions.

1. Background

1.1. Urban Heat Island

UHI is the name given to describe the characteristics of warmth for both the atmospheres and surfaces in cities (urban areas) compared to their (non-urbanized) surroundings. UHI is a result of densely built infrastructures of cities that absorb and trap solar radiation and traffic generated heat and retains the heat for periods longer than natural surfaces. Urban heat island affects street level thermal comfort, health and environment quality and may cause increase of energy demand.

Heat island is caused by urbanization when urban surfaces (buildings, roads, pavements) store heat during daytime and release it during night-time into urban canyon, keeping urban areas hotter than their surroundings. Heat island affects urban canopy, cities' energy use and habitability [1]. It has been widely acknowledged that urban surfaces tend to absorb significant amount of solar radiation and release it as heat, due to the thermal properties of common building and pavement materials. Urban morphology parameters (e.g. pavement area, building height, wall surface area, green plot ratio, sky view factor) also



influence the microclimate in terms of the solar access and wind speed [2]. Anthropogenic heat released from traffic and building HVAC systems further heats up the environment in the street canyons.

UHI in cities can be quantified by measuring UHI intensity, which refers to difference between background rural and highest urban temperature. In Singapore, the satellite image shows UHI effect during daytime. The ‘hot’ spots are normally observed on exposed hard surfaces in urban context, such as industrial area, airport and Central Business District (CBD). The satellite image also shows some ‘cool’ spots, which are mostly observed on the large parks, the landscape in-between the housing estates and the catchment area [3].

The annual average surface temperature in Singapore has increased from 26.6°C in 1972 to 27.7°C in 2014. It is predicted to rise by 1.4-4.6°C by 2099 in the context of global warming. The UHI effect that a city area that is significantly warmer than its surrounding rural areas is also found quite evident. The densely built urban areas, such as central business district (CBD) area, is up to 4°C hotter than green spaces (e.g. parks, forests, catchment areas, etc.) during hot afternoons. The daytime UHI intensity on National University of Singapore (NUS) campus was found as high as 3°C at around 3 pm [4-7].

1.2. Importance of canopy modelling on different scales

The attention on UHI and microclimate issues has helped to advance the development of urban cooling strategies in Singapore. Some strategies have been proved effective in UHI mitigation, such as providing parks and trees, better street canyon ventilation, green roofs and walls, phase change and ‘cool’ materials, self-shading building envelopes, etc. However, these urban cooling strategies are often implemented at different levels with different mechanisms, and studies on the environmental implications of these strategies are often segregated.

Therefore, in order to mitigate the UHI in Singapore, it is necessary to have a comprehensive understanding on how the urban canopy works. Canopy modelling plays a vital role in estimating weather conditions within an urban area, such as ambient temperature. However, the ambient temperature in urban environment is very dynamic, due to the influence of various environmental factors in the following aspects:

- *Regional climate*: solar radiation, seasonal wind and direction, humidity, etc.
- *Urban morphology*: greenery, building density, road pattern, canyon width, sky view factor, water, etc.
- *Building and pavement material properties*: reflectivity, emissivity, heat capacity, etc.
- *Anthropogenic heat*: vehicle exhausts, HVAC system, human metabolism, etc.

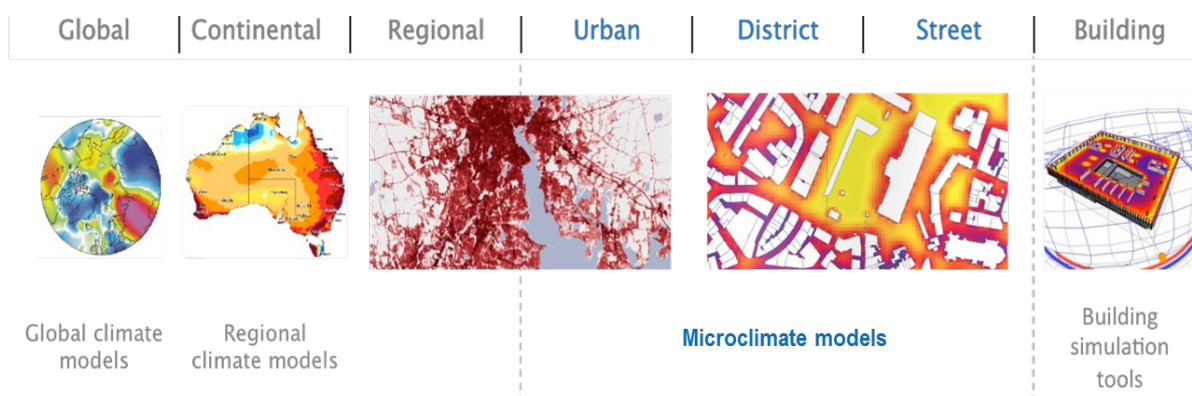


Figure 1. Climate modelling at different levels

So far, two categories of methods have been tested in Singapore to analyse urban canopy: empirically based models, and physically based models. While empirically based models were developed from experiments conducted in Singapore, physically based models rely on fundamental heat transfer and thermodynamic theories to assess ambient temperature, or any other weather parameter. However, both empirically and physically based urban climatic models still lack in interacting with higher scale climatic models to assess conditions at the urban boundary layer. It is thus become imperative to develop an integrated model for accurate prediction of weather conditions at different scales. Figure 1 illustrates prospects of a full climatic models and the different scales it should consider.

1.3. Integrating various tools of research into a single platform

Current priorities placed on sustainable urban development have encouraged urban planners to examine the various parameters of urban canopy modelling and incorporate them into planning and design efforts. But while they may understand the importance of interactions between urban morphology and urban microclimate condition, they lack basic knowledge of urban climatology. Engaging urban climate scientists to conduct assessments and provide feedback has helped inform design and planning efforts, but to date the design process has been largely decoupled from the impact assessment and analysis process [8, 9].

The integration of urban planning and design tools with urban microclimate assessment tools is a complex endeavour but one with a promising future. This integration will integrate urban climatic assessment as part of the urban design process. Urban planners will be able to assess the impact of their designs, i.e., the change of urban morphology, to the urban climatic condition simultaneously without separately engaging scientists.

As part of the ongoing research project, the above-mentioned platform, which is called Building Energy Simulation and Urban Canopy Modelling or BESCAM, will utilize Virtual Singapore (VSg), a three-dimensional city model of Singapore, established and developed by National Research Foundation (NRF), Prime Minister's Office, Singapore, the Singapore Land Authority (SLA) and the Government Technology Agency of Singapore (GovTech). The aim of this Virtual Singapore project is to achieve a 3D digital platform that will "enable users from different sectors to develop sophisticated tools and applications for test-bedding concepts and services, planning and decision-making, and research on technologies to solve emerging and complex challenges for Singapore" [10].

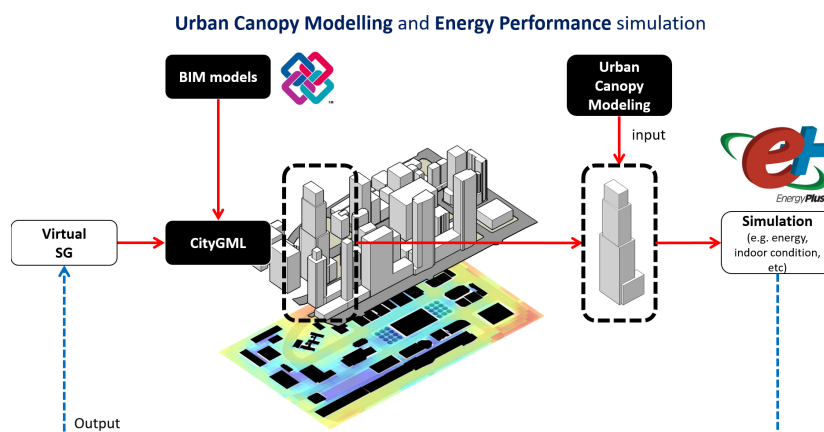


Figure 2. Workflow for BESCAM.

2. BESCAM methodology

Figure 2 illustrates the workflow methodology of BESCAM to achieve the main objective, which is to develop a platform to perform energy simulation at building level by implementing UCM and using VSg building models, converted from BIM, as input. Currently, BESCAM is still in the early stage of:

- BIM conversion into CityGML
- UCM development, and
- Urban-scale microclimate analysis method.

Hence, the following discussion focuses on those three components.

3. Mapping and conversion of IFC-BIM models into CityGML.

BESCAM will use the urban geometry models from VSg, which are the converted IFC-BIM models. This process refers to the on-going project “Strict and automatic mapping of IFC-BIM models into semantically enriched 3D CityGML building models (exterior and interior)”, as seen in which is the development of a methodology and algorithms to automate the mapping and conversion of IFC-BIM models into CityGML building models while ensuring a complete and near-lossless mapping [11]. The mapping will capture both geometric and semantic information as available in the IFC-BIM models, in order to create semantically enriched 3D city models and to extend these city models to include exterior as well as interior structures such as corridors, rooms, internal doors, and stairs. A formal ontology will be developed for both IFC and CityGML and a semantic mapping between the two data models based on this ontology, as part of a formal framework for strict (semantic and geometric) conversion that supports models to be automatically exchanged. This framework will include an identification of the necessary transformations to convert IFC geometry data into CityGML geometry, as well as the ability to assign semantic data from the IFC building model into elements of the CityGML model.

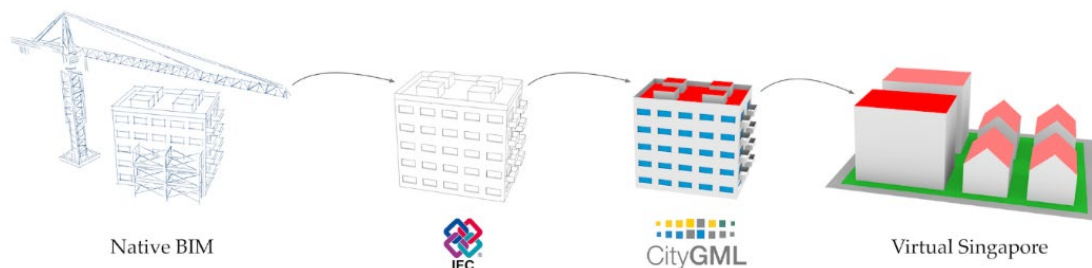


Figure 3. The workflow from native BIM (Building Information Model) to the integration of CityGML models in Virtual Singapore [11]

This research will draw upon literature on formal approaches for semantic and geometric conversion between IFC and CityGML, and will also consider user requirements, specifically from Housing Development Board (HDB) and Building and Construction Authority (BCA) as collaborators in this project, such as the practice at HDB to convert from CityGML to the STL format to support computational fluid dynamics (CFD) wind simulations. While conversions from CityGML to other formats will not be developed within this project, requirements on a CityGML model relating to such conversions, such as the need to identify the relationship between a window and the wall it belongs to in the CityGML model, will be considered.

The mapping between the two data models, including the necessary transformations as identified, will be translated into conversion algorithms and software routines that allow a near-complete and near-lossless automated mapping from IFC-BIM to CityGML. The completeness will depend on the ability to implement necessary updates to standards and specifications. The development of the conversion algorithms will draw upon an existing open source solution to automatically generate CityGML LoD3 building models from IFC models. The methodology and algorithms will specifically target the conversion of IFC-BIM models, not BIM models in any native format as used by these BIM applications. Nevertheless, as BIM applications translate their BIM models into IFC, while using the same format, there are variations in how the models are specified in IFC. Testing with a variety of IFC-BIM models is meant to address these variations.

4. Integration of CityGML and BIM into a physically-based urban microclimate model

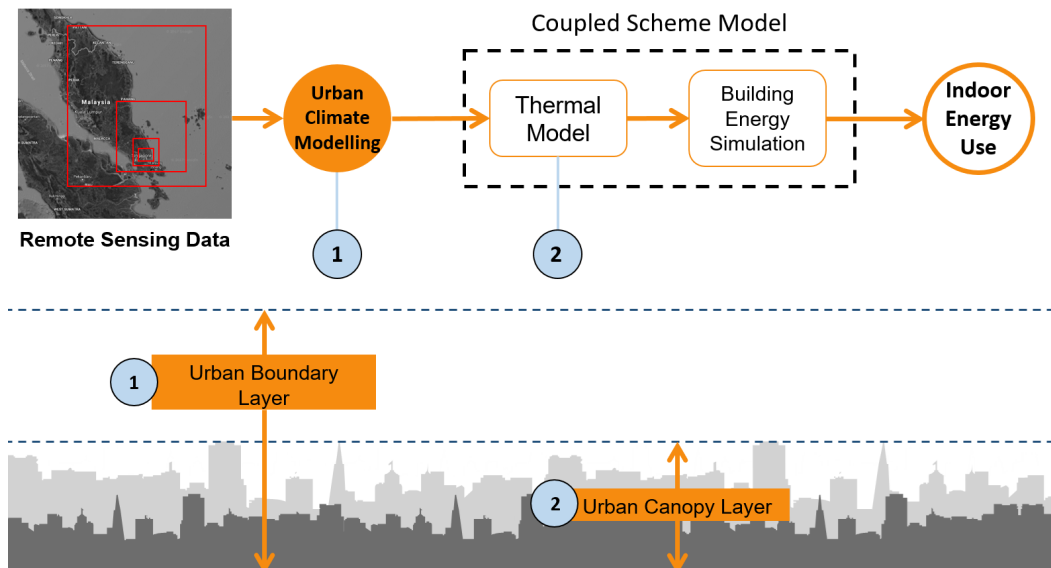


Figure 4. The proposed urban canopy modelling, which links global, urban, and building scale.

After scaling down the climate variables up to city scale, a coupled scheme model is implemented as boundary condition to conduct building energy simulation to study the indoor energy use (see Figure 4). At the building scale, the simulation of building energy consumption has been the main focus, e.g., EnergyPlus, Revit, IES-VE, and TRANSES. By default, these detailed building energy models assume that the weather conditions are uniformly distributed around the reference building. Consequently, the external heat gain of building envelope is not properly evaluated, and the effects of shading, greenery, anthropogenic heat or building surface materials on ambient temperature are often neglected. Hence, the relationship between the outdoor and indoor air quality is also often neglected.

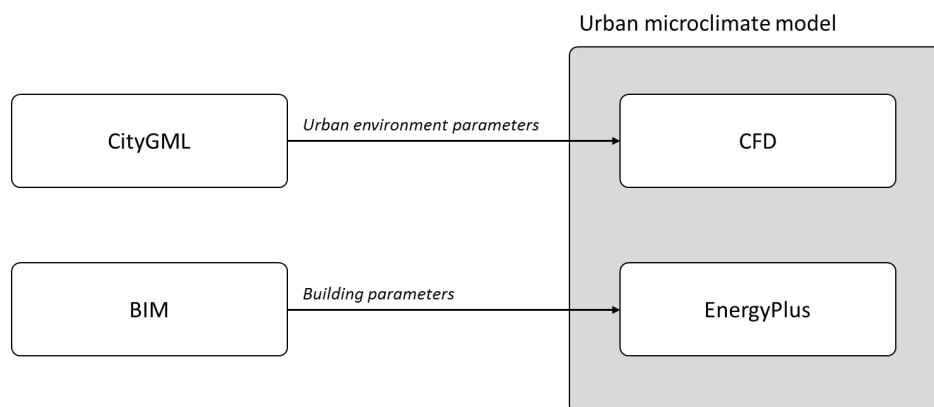


Figure 5. Integration of CityGML and BIM models into a physically-based urban microclimate model for the assessment of weather conditions and building energy use.

CityGML and BIM models exported from the VSg platform are used to parametrize a physically-based urban microclimate model, as illustrated in Figure 5. This model consists of a Computational Fluid Dynamics (CFD) model to assess weather conditions of the outdoor environment and an EnergyPlus model to simulate the energy use of a specific building. On one hand, information stored in a CityGML model, like properties of surrounding buildings and street pavements, are used to establish

CFD simulations of weather conditions at the urban microscale. The EnergyPlus model, on the other hand, is generated from the BIM model of the reference building.

The objective of this method is to compute weather conditions that surrounds a specific building, hence the building energy simulation can be conducted with proper microclimatic data for better estimation of heat transfer process, which determines the UHI impact on buildings. Moreover, planners will be able to evaluate energy savings achieved by UHI mitigation strategies that are defined within the urban canopy model.

Boundary conditions of the CFD model and EnergyPlus model are defined through a coupling process. While weather conditions and convective heat transfer coefficients are evaluated from CFD simulations, the EnergyPlus model provides estimates of the surface temperature of the reference building and anthropogenic heat releases caused using energy in the indoor space. Atmospheric conditions are in addition specified as boundary conditions of CFD simulations. They are obtained from the use of a mesoscale climatic model. Figure 6 shows the various components of the physically-based urban microclimate model.

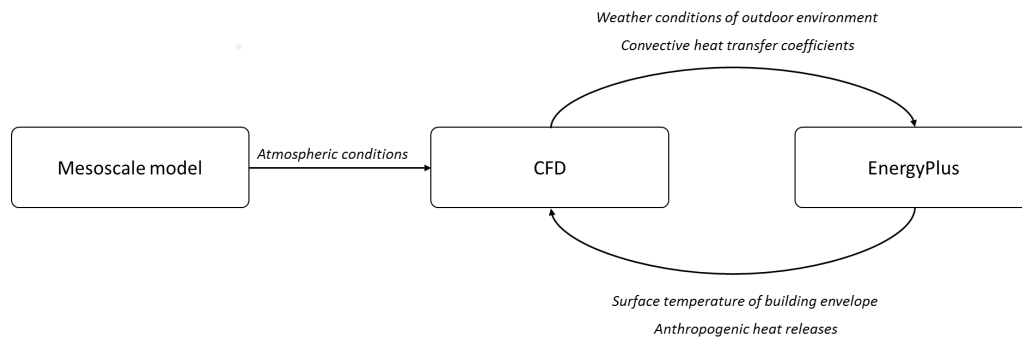


Figure 6. Physically-based urban microclimate model.

5. Investigation of existing temperature prediction models

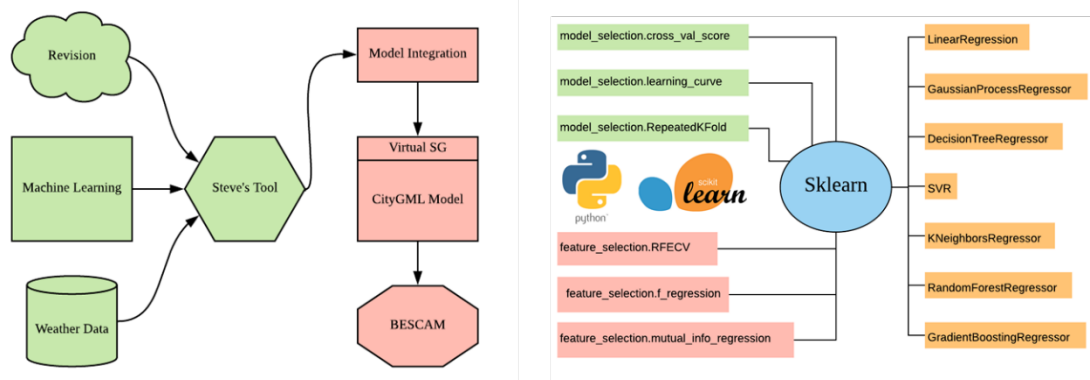


Figure 7. Integration processes and overview of machine learning algorithms.

Data analysis is no stranger to the scientific community. Today, with the rapid development of computer hardware, advanced analysis algorithms such as machine learning have reached the stage of helping scientists solve the most difficult data analysis problems. Prediction of urban microclimate is a typical non-linear problem influenced by many factors including individual building, urban morphology and weather of city. It is a combination of multi physics phenomenon such as airflow, heat transfer, radiation and air pollution. Previously, Jusuf and Wong [12, 13] proposed a set of linear regression models to estimate temperatures based on reference weather data and urban morphology parameters at estate level. The models, called The Screening Tool for Estate Environment Evaluation (STEVE) was developed

with the intention of bridging research findings, especially those of air temperature prediction models and of urban planners. STEVE was initially developed as a Geographical Information System (GIS) plugin, then was altered into SketchUp plugin, to accommodate designers and users that is more accustomed with SketchUp's 3D modelling environment.

The air temperature prediction models can calculate the daily minimum (T_{min}), average (T_{avg}) and maximum (T_{max}) temperature of each point of measurement based on climate predictors and urban morphology predictors. The climate predictors are daily minimum temperature (T_{min-r}) at reference point, daily average (T_{avg-r}) temperature at reference point, maximum (T_{max-r}) temperature at reference point, average of daily solar radiation total (SOLAR_{total}), and average of solar radiation maximum (SOLAR_{max}); while the urban morphology predictors are percentage of pavement area over surface area (PAVE), average height to building area ratio (HBDG), total wall surface area (WALL), Green Plot Ratio (GnPR), SVF and average surface albedo (ALB) [14].

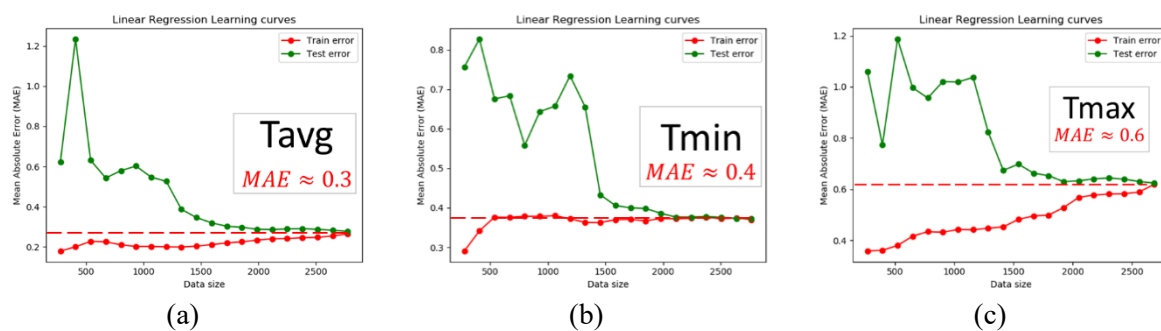


Figure 8. Learning curves of linear regression model of original STEVE tool: (a) Average temperature prediction; (b) Minimum temperature prediction; (c) Maximum temperature prediction.

In this part of the research project, the goal is to enhance STEVE tool using state-of-the-art machine learning algorithms (Figure 7). Python was selected as programming language because of extensive support libraries and user-friendly data structures. In addition, the open source machine learning library Scikit-Learn [15] was utilized since it is accessed from Python and covers a wide range of machine learning algorithms. The preliminary investigation was organized as follows. First, cross-validation re-evaluated the original STEVE tool to predict the performance of the algorithm on the unseen data. Then, several machine learning algorithms were selected from the Scikit-learn and tested on the weather data. Finally, the optimal algorithm was chosen based on accuracy and improvement potential.

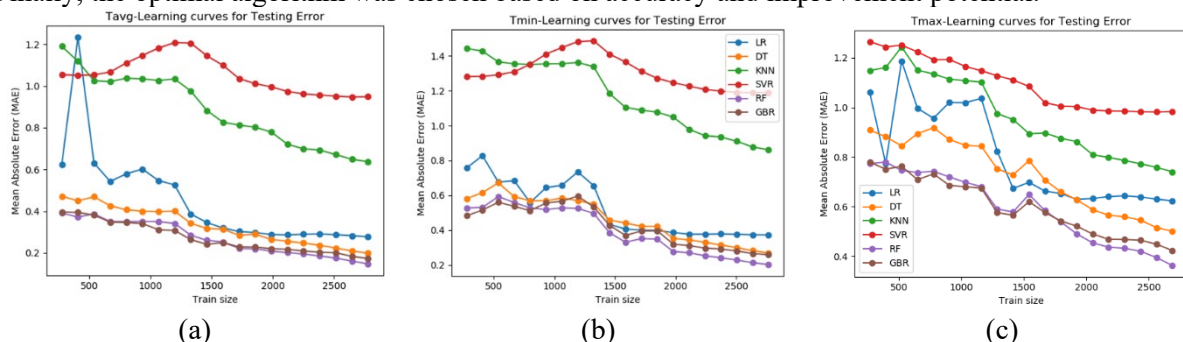


Figure 9. Comparison Of machine learning algorithms' testing error performance: (a) Average temperature prediction; (b) Minimum temperature prediction; (c) Maximum temperature prediction.

In the beginning, the prediction accuracy of original STEVE tool was evaluated by the repeated K-fold cross validation [16] which was algorithm-based method used to evaluate the algorithm's prediction performance on unseen data. Learning curves of train and test error are commonly used in machine learning to evaluate the algorithm's response to the data size [17]. Based on the learning curves (Figure 8), it was found that the original linear model had mean absolute error (MAE) of the test data ranging

from 0.3 to 0.6 °C. Considering the small difference of daily air temperature in Singapore, the error was quite significant. In addition, the training and test curves converged at full-scale data meaning providing more training data was not useful for improving model accuracy. Therefore, there was a need to find better algorithms for estate level air temperature prediction.

Afterwards, multiple machine learning algorithms were tested to find the optimum model for the prediction of urban microclimate (Figure 9). The results show that machine learning algorithms such as support vector machine (SVM) and k-nearest neighbour (KNN) were not suitable for temperature prediction while tree-based algorithms such as decision trees or random forests outperformed linear regression in predicting the air temperature. The reason may be since tree-based algorithms are better at discrete attributes that exist in the collection of urban morphology data.

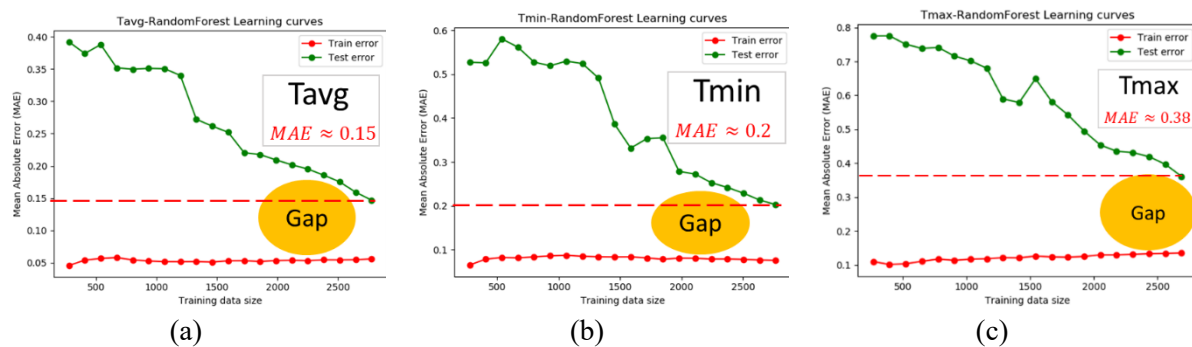


Figure 10. Learning curves of random forest model: (a) Average temperature prediction; (b) Minimum temperature prediction; (c) Maximum temperature prediction.

Random forest [18] had low bias on the prediction results that error was reduced around 50% compared to linear model (Figure 10). Moreover, learning curves were not converged suggesting a space for model improvement. In the next stage, we will further enhance random forest model by adding more training instance, adding more features, doing feature selection or hyperparameter optimization.

6. Future work

6.1. Developing model of interactions between urban microclimate and building energy use

Various improvements were achieved in the development of a physically-based model to simulate interactions between urban microclimate and building energy use; this platform will be called UMBER. First, the domain object model, that is the structure of data to be stored and manipulated in the UMBER model, was defined such as determining what information will be required from CityGML and BIM models. To facilitate the integration of CityGML and BIM models into the physically-based model, an appropriate software architecture was thought making a good use of software design patterns. The software architecture being implemented aims at including High Performance Computational (HPC) resources to minimize the runtime of simulations of the model.

The software architecture of the UMBER simulation engine is primarily composed of front-end and back-end components. The front-end consists of the Core software component of the simulation engine, which will be implemented in MATLAB and running in a Windows environment. The Core component will essentially be responsible of synchronizing and processing the inputs/outputs of the EnergyPlus model of the reference building through the BCTVB middleware. A Java client will be developed for the Core component to communicate with the back-end application, which is meant to be running in an HPC. For this reason, python and Linux are the technology used to develop the back-end application. To synchronize and process inputs/outputs of OpenFOAM simulations of urban microclimate conditions, an UMBER-server component is being implemented. Figure 11 summarises the software architecture of the UMBER simulation engine.

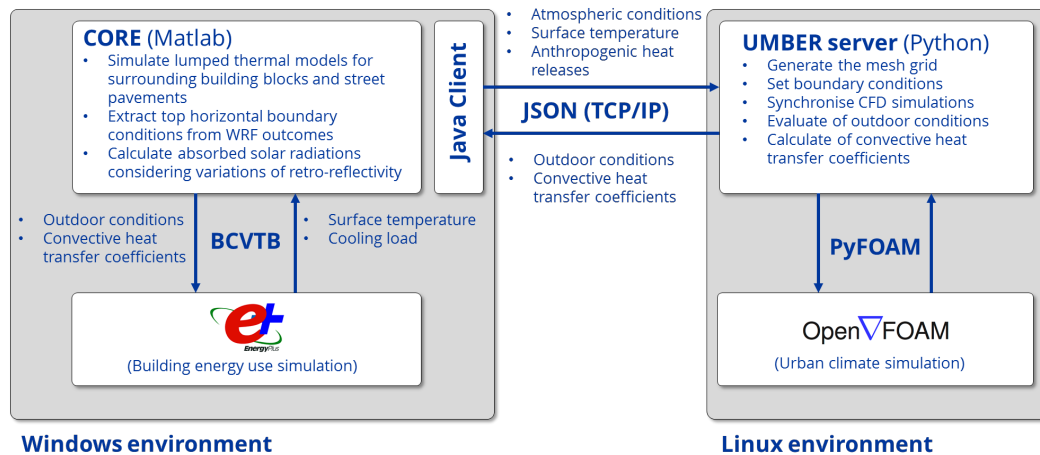


Figure 11. Software architecture of the UMBER simulation engine.

6.2. Temperature prediction models

In the next stage, the air temperature prediction model will go through the optimization processes. The objective is to minimize the discrepancy caused by the model rather than the training data. As discussed in the previous sections, machine learning model can be further improved if the learning curves are not converged at the full size of the data. Normally, there are four approaches available for optimization including increase of data size, increase of input feature, input feature selection, and hyperparameter tuning.

First, feature selection will be conducted to select the most relevant features for the prediction model. Recursive feature elimination, F-regression and mutual information are three techniques commonly used to test the correlation of each feature with the outcome variable. The hyperparameters of the random forest algorithm will be optimized after feature selection. In machine learning, hyperparameter refers to the parameter whose value is set before the learning process begins. The search of optimal hyperparameter of a learning algorithm is to minimize a predefined loss function. Potential candidates of tuning approach are grid search and random search coupled with cross validation. Although machine learning model is evaluated using cross validation, the research group will provide another validation data set which is completely outside the original training and testing data to double verify the model accuracy.

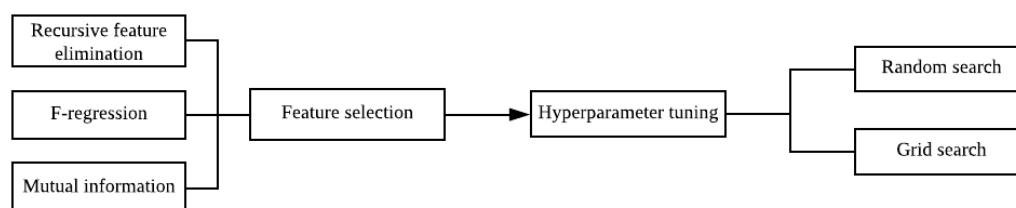


Figure 12. Two processes for optimization of machine learning model

7. Conclusion

As BESCAM is still in the development process, this paper highlights some of the important components and fundamental methods on urban canopy modelling integration with building energy performance. Compared to what has been achieved in the other studies, the BESCAM platform would offer a unique opportunity to local architects, engineers, and scientists to use the same source of information, using VSg database, for conducting their own analysis and compare their conclusions. Furthermore, this platform would simulate weather conditions from the city scale to the building scale taking into consideration major anthropogenic heat sources.

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