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Pathway using WUDAPT's Digital Synthetic City tool towards generating urban canopy parameters for multi-scale urban atmospheric modeling

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A B S T R A C T

The WUDAPT (World Urban Database and Access Portal Tools project goal is to capture consistent information on urban form and function for cities worldwide that can support urban weather, climate, hydrology and air quality modeling. These data are provided as urban canopy parameters (UCPs) as used by weather, climate and air quality models to simulate the effects of urban surfaces on the overlying atmosphere. Information is stored with different levels of detail (LOD). With higher LOD greater spatial precision is provided. At the lowest LOD, Local Climate Zones (LCZ) with nominal UCP ranges is provided (order 100 m or more). To describe the spatial heterogeneity present in cities with great specificity at different urban scales we introduce the Digital Synthetic City (DSC) tool to generate UCPs at any desired scale meeting the fit-for-purpose goal of WUDAPT. 3D building and road elements of entire city landscapes are simulated based on readily available data. Comparisons with real-world urban data are very encouraging. It is customized (C-DSC) to incorporate each city's unique building morphologies based on unique types, variations and spatial distribution of building typologies, architecture features, construction materials and distribution of green and pervious surfaces. The C-DSC uses crowdsourcing methods and sampling within city Testbeds from around the world. UCP data can be computed from synthetic images at selected grid sizes and stored such that the coded string provides UCP values for individual grid cells.

1. Introduction

Cities are unique and important to climate science for a number of reasons. While geographically occupying only a small proportion of the planet's available land area, they house most of humanity and are the focus of resource usage and waste products. The profound landscape change that accompanies urbanization radically alters local environments, creating urban heat islands and exacerbating weather extremes such as urban flooding and heat waves (Revi et al., 2014, Li and Bou-Zeid, 2013, Siu and Hart, 2013, Niyogi et al. 2017 and Hunt et al. 2018). Sustaining cities requires the transfer of resources (water, materials, energy, etc.), some of which are stored for a period of time but most of which are returned as wastes to the environment, resulting in poor air quality at local/regional scales and modifying the chemical composition of their atmosphere at regional and global scales. Cities also tend to be located in places that are exposed to natural hazards (such as coastal flooding); their risks will be accentuated in global climate change scenarios. To summarize: cities affect (and are impacted by) climate at a hierarchy of scales; the nature of this relationship depends on the city-specific urban form and function, and the outcome varies depending on the city's geographic and topographic situation, their climate and weather regime. It follows then that addressing climate-driven mitigation and adaptation at urban scales requires a scientific framework that includes models capable of responding to the unique characteristics of individual cities. Such models are needed to support current and emerging climate and environment policy and action plans that have immense socio-economic and political implications (Ng, 2010; Ren et al., 2011, 2018; Masson et al., 2014; Ng and Ren, 2018; Baklanov et al., 2016; Ching et al., 2018; Creutzig et al., 2018; See et al., 2015b; Brown, 2000,Zhang et al. 2010b).

In the past few decades, urban climate science has made substantive progress towards meeting these needs. The infrastructure of this science has been constructed through the judicious application of atmospheric physics appropriate to urban micro- and meso-scale, carefully designed field experiments (Grimmond et al. 2010) to test and evaluate the application of boundary-layer theory to the complex and heterogeneous urban environment (Fig. 1) and numerical descriptions of the urban landscape referred to hereafter as urban canopy parameters or UCPs (Brown and Williams, 1998; Brown, 2000;Chen et al., 2010; Jackson et al., 2010; Feddema et al., 2015; Ching et al., 2016). Available now are a suite of advanced modeling systems, many are publicly available and have common characteristics: universal availability; upgrades and support; solid foundation in science process descriptions and applicability to a range of urban simulations. A prominent example is the Weather Research and Forecasting model WRF (Chen et al., 2010) and its extensions that incorporate atmospheric chemistry such as CMAQ (https://www.cmascenter.org, WRF Chem (https://www2.acom.ucar.edu/wrf-chem) (Dirce et al., 2018 and Dai et al., 2018) and urban landscapes. Another is the Urban Multi-scale Environmental Predictor (UMEP), which is a climate service tool designed for researchers and service providers (e.g. architects, climatologists, energy, health and urban planners Lindberg et al. (2017, 2018). The need for improved models that can be integrated into decision-making action oriented activities at urban scales will continue to grow e.g., (Masson et al. 2014), and also given the recent WMO mandate and urgency for integrated urban weather, climate, hydrology and related environment services (Baklanov et al., 2015, 2018; WMO, 2015).

Despite the advances in urban climate science, gaps remain. Notably much of our knowledge is based on a few places with model simulations evaluated by even more limited observations. Generally, we know little worldwide on city form and functions or the UCP

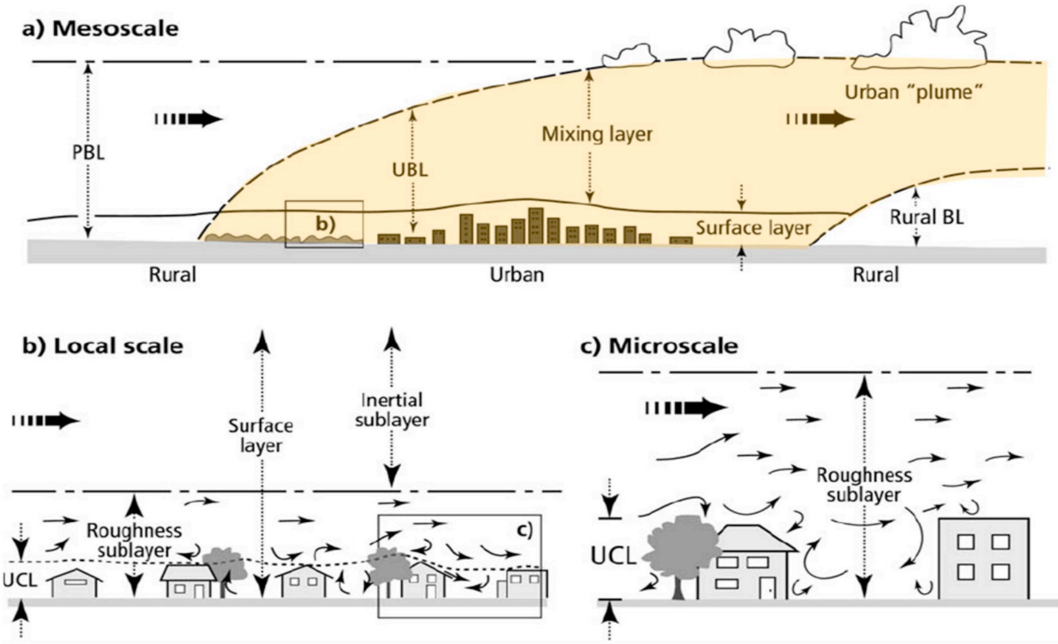

Fig. 1. Schematic of Urban Boundary Layer (from Oke et al., 2017, 'Urban Environments' in W.G. Bailey, T.R. Oke and W. R. Rouse (eds) The Surface Climates of Canada, McGill-Queens's University Press, Montreal, 303–327).

model inputs (Table 1) needed for state-of-the-art science models. A major obstacle to the general application of the accumulated knowledge that is available in modern models is the absence of UCP and observations; such data should be relevant, consistent and coherent so that city landscapes can be compared. The WUDAPT project strives to improve coverage and quality data describing the underlying urban surface, so as to improve modeling and understanding of urban processes (Mills et al. 2015, 2017a,b; See et al., 2015a; Ching, 2013,Ching et al., 2015, 2016, 2017a,b;Ching et al., 2018).

In this paper, we address the need for a common set of model parameters to adequately describe the urban canopy layer (Fig. 1) and therefore support several important categories of science-based models and their corresponding 'fitness for purpose' applications. Within the WUDAPT methodology to acquire and structure data we employ bold heuristic approaches and innovations within a community-based framework. This paper concludes with examples of progress and future expectations and activities (Ren et al., 2013).

2. Overview: a fit-for-purpose modeling framework

Mesoscale atmospheric models simulate exchanges using a spatial domain divided into vertical layers and horizontal grids.

Table 1
Urban canopy parameters (UCP) commonly used across a wide range of modern urban -atmosphere process models. Different metrics (*) may be of interest for example: mean, standard deviation, maximum, variance, distribution. Some UCP (+) are not fundamental and therefore have more assumption within them.

Land Cover	Typology	UCPs
Impervious Fraction	Buildings	Building height*
Buildings	Typology class, age	Building width*
Roads	Building Types, age	Street width *
Other	Number of Floors	Mean Aspect Ratio
Pervious Fraction	HVAC	SVF (bldg. only) * +
Lawn	Glazing Ratio	SVF (w/trees) * +
Trees and Shrubs	Anthropogenic heating	Dominant street orientation
Bare area	Roof Material	Building Volume to Area*
Recreation	Wall material	Frontal Area Density
Water	Reflectance/Albedo	Plan area density
	Thermal admittance	Roughness length +
	Vegetative Class	Displacement height +
	Trees (Tall > 2 m)	
	Shrubs	
	Irrigation	

Typically the vertical layers vary with the shallowest layers close to the surface where exchanges are intense. Horizontal grids, frequently uniform in size, are orders of magnitude larger than Δz. The model cell size is selected to capture the important processes and time scales. Parameterization schemes are needed for some processes. Grid nesting may be used to improve spatial resolution. In urban areas, the underlying urban fabric and human activities pose considerable added challenges to developing parameterizations to appropriately capture the scaling essence of relevant processes impacted by changes to the underlying surfaces. The optimal model design application principle is for the grid scale to be commensurate and appropriate to the resolution needs of their application. Model parameters provide a means to describe the underlying fundamental boundary layer flow, turbulence, energy and chemical vertical exchange processes. A design requirement is that these descriptions need to be appropriate to the scale of the problem and application, giving meaning to being 'fit for purpose' (Baklanov et al., 2009). Thus, the study purpose, CPU limitations, and input data available, should guide model choice, resolution, and level of detail needed for the input parameters.

2.1. *Urban climate and environmental models and their data needs*

Current models for boundary layer flows over horizontally relative uniform surfaces use Monin-Obukhov Similarity Theory (MOST), with roughness (z_0) and stability (L) length scales to describe surface impacts on momentum, heat, and other surface to atmosphere gas and aerosol exchanges. However, urban surfaces are often highly spatially heterogeneous with natural and constructed features commingled with anthropogenic sources of heat, vapor, and chemicals. This heterogeneity produces immense varieties and distributions of microclimates within the urban canopy layer (Fig. 1) and controls the temporal and spatial structure of the overlying boundary layer and vertical exchanges of momentum (i.e., drag), sensible, latent, radiant heat (Grimmond and Oke 1999,Grimmond et al., 2010) and of chemical species of pollutants and GHGs (Mouzourides et al. 2018) (Fig. 2). To capture the essence of these processes, the urban landscape is described using UCPs and relevant land cover and typological features for running and applying urban models (Table 1). This was accomplished using the paradigm of Local Climate Zones and their corresponding lookup tables for UCPs (Stewart and Oke, 2012) in Level 0, and the more general grid specific approach to be describe herein in Level 1 and 2.

The UCP inform the modeling of climatic impacts of various morphological elements of the urban landscape, classified by scale from facets, blocks and neighborhoods (Fig. 3). Facets, at their most detailed, are surfaces (fixed orientation and slope) comprised of the same material (natural or manufactured). Building envelopes are composed of individual facets. Buildings and trees are the primary 3-D objects. Streets and blocks describe the layout of facets, buildings and trees that make up the urban land cover. Neighborhoods are the typical layouts that characterize different urban land uses, such as residential or commercial. Each building, street, block and neighbourhood is linked with a range of functions (transport, heating/cooling, lighting, manufacturing, etc.) that generates waste heat, energy, water and materials into the overlying atmosphere. Taken together these attributes can be classified into urban form and function related UCP. They distill the aerodynamic characteristics of site, which get these variables into numerical values representing roughness, impervious land cover, thermal admittance, albedo, etc. that are employed in climate models (Grimmond and Oke, 1999; Oleson et al., 2008). In WUDAPT, we consider the set of parameters listed in Table 1 that are practical to generate, and sufficient and adequate for a wide range and "fit-for most purposes" applications, hopefully, refined treatments and other combinations and perturbations of this set of UCPs are possible. Comprehensive discussions and explanations about such parameters and their implementation in models can be found in Brown and Williams (1998), Brown (2000), Jarvi et al. (2011),Masson (2000), Martilli et al. (2002); Kusaka et al., 2001, Kusaka and Kimura, 2004, Dupont et al. (2004), Otte et al. (2004), Baklanov et al. (2009), Jackson et al. (2010), Lemonsu et al. (2012),Chen et al. (2012),Chan et al. (2013), Garuma (2018), Oke et al. (2017), Pigeon et al. (2014),Schoetter et al. (2017),Yang et al. (2012) and Shi et al. (2018). Already, we anticipate its utility as an infrastructure that can support the goals outlined in the recently issued WMO Guide for Integrated Urban Services (WMO, 2018), a global program of integrated urban weather, water, environment and climate services using various fit-for-purpose models by stakeholders for cities towards their sustainable development, considering general requirements for observations, data, databases and data sharing for urban modeling and prediction capabilities for different urban service applications. Such services should assist cities

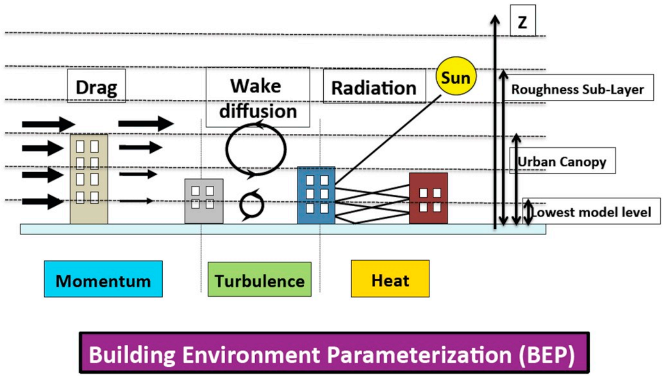

Fig. 2. Models embodying urban climate knowledge.

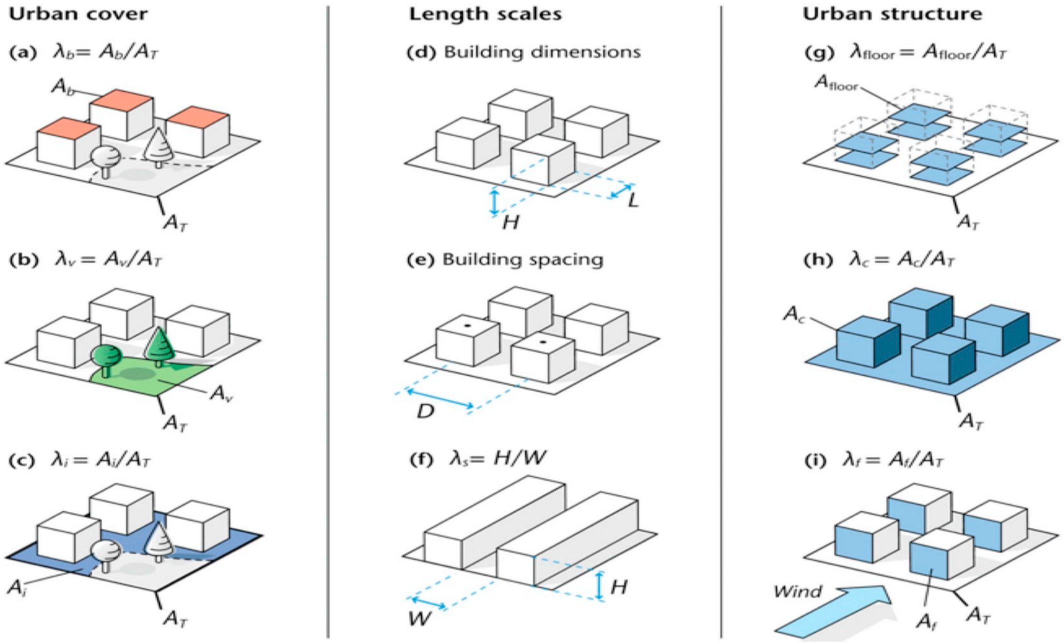

Fig. 3. Form-based Urban Canopy Parameters (from Oke et al., 2017).

in facing hazards as varied as storm surges, flooding, heat waves, and air pollution episodes, especially in changing climates, while making the best use of science and technology and considering the challenge of delivering such services to end-users. Their aim is to build services that meet the special needs of cities through a combination of dense observation networks, high-resolution forecasts, multi-hazard early warning systems, and climate services for mitigation and adaptation strategies that will enable the creation of resilient and sustainable cities in different regions around the world. WUDAPT's goal is to achieve worldwide coverage for any and all major cities of these UCPs to support their atmospheric modeling needs at varying scales in timely fashion, globally. A variety of model applications are presented in Section 3.4 utilizing W1&2 data, in Appendix A and Table 4.

2.2. WUDAPT data

Table 2 depicts WUDAPT's hierarchical approach to generating UCPs. Level 0 (L0) data are based on satellite imagery, which are categorized into Local Climate Zone (LCZ) types, based upon combinations of building height, packing of roughness elements (building and trees), perviousness of surrounding morphology elements and materials. Each LCZ class has associated lookup tables of UCPs (Stewart and Oke, 2012). The methodology for generating LCZ maps has been developed, tested by Bechtel and Daneke, 2012, Bechtel et al., 2015, 2017a, 2017b) and Zheng et al. (2018), and a summary of the approach is described in Mills et al. (2015) and

Table 2
WUDAPT Levels 0, 1 & 2 features and their potential applications.

Product	Level 0	Level 1	Level 2
Coverage	Over 120 cities and regions	Data gathering methods; and testing to refine Level 0 based on crowdsourcing APPS and Buidling Typology approaches as in MApUCE	Any city by using our new 3-D mapping technology, DSC
Data source	Landsat + Google Earth + local data & expert evaluation	Landsat + Google Earth + local data & expert evaluation	World-view Stereo Data + Terra-SAR data
Resolution	100–500 m	100–500 m	2 m
Format	kml, tiff	GIS shapefiles	GIS shapefiles
Applications	Environment and Energy (Weather Research and Forecasting (WRF) Modeling, Urban heat island) Urban and Regional planning (population density)	Environment and Energy (weather and climate, urban air flows, urban radiation, mean radiant temperature, urban energy consumption, air pollution, CO2 and GHG emission) Ecology (biodiversity) Urban and Regional planning (master plan, land use plan, green master plan, new town plan)	Environment and Energy (building energy cost) Building and community design (visibility analysis, building development) Disaster and risk management (Flooding, heatwave) Pedestrian and citizen's mobility (walkability, thermal comfort) Public health (polluted areas)

Ching et al. (2018). There are 17 basic LCZ types that include 10 urban and 7 natural types - each type is associated with a tabulated range of appropriate UCP values. The WUDAPT process relies on urban experts to provide the training areas needed to create L0 data, which consists of a grid map of the city and its surrounds in which each cell is classified into an LCZ type. These maps can be converted into matrices of UCP values that can be used in models (Ching et al., 2018). However, this approach has its limits, for example, the LCZ scheme provides associated ranges of UCP values for each LCZ type. Subsequently, the user can assign either LCZ default values to each LCZ type or some other prescriptive means for the modeling domain. The objective of the higher levels in the WUDAPT scheme is designed to provide explicit multiscale gridded values for each and all UCPs based on a consistent and standardized framework. Level 1 (L1) data may be acquired by spatial sampling, using L0 (LCZ) data as a frame to ensure that the urban landscapes within the modeling domain are sampled appropriately. Level 2 (L2) data can be described as complete coverage based on information gathered across the entire domain. Fundamental to both is information on the basic elements (buildings, trees, roads, etc.) of urbanized landscapes. For *meso*scale urban models, the goal is the generation of specific UCP values to support the full suite of 'fit for purpose' block-to-meso scale weather and climate models. As a template, historically, the National Urban Database Access Tools (NUDAPT) project provides L2 information for parts of a number of North American cities where detailed municipal data are available on individual building footprints, heights and materials; see, for example, Ching et al. (2009). However, this type and level of information is not generally available and is still currently relatively expensive and difficult to generate with currently available methods.

In contrast to NUDAPT, WUDAPT is developing an innovative approach to generate L1/L2 data that are consistent and universally applicable, practical, pragmatic and timely to implement, relies on freely and readily available data and satisfies the modeling requirements discussed earlier. These include a suite of tools to generate different UCPs and Testbeds, sets of cities where independently derived data can be used to evaluate and improve these tools. Specific elements and issues of this approach towards the goal of producing, testing establishing and making available a community based data generating methodology and protocol is outlined and described in the next section. This is followed by some preliminary results and a discussion of next steps.

3. Conceptual framework for deriving level 1&2 data

3.1. Overview

Where detailed municipal data on buildings, roads, vegetation, etc. exist (e.g. NUDAPT information), UCPs can be calculated at a selected level of precision. However, our objective is to generate equivalent urban scale UCP data ab initio, that is generated on a consistent basis anywhere in the world, with readily available data that can be generated by the urban community in a practical and useful timeframe for actionable science-policy utility, and whose output is of known quality, unrestricted, and publicly available. The approach taken in WUDAPT Level 1 and 2 is designed to meet these challenges. The conceptual framework for deriving WUDAPT Level 1&2 data is shown in Fig. 4. At its core is the Digital Synthetic City (DSC) tool, which simulates the spatial heterogeneity that characterizes urban landscapes at an urban block scale. The generic DSC has the capacity and will be "customized" to include the types of buildings (and materials) associated with cultural and historical practices that distinguish places. It is proposed that these building-scale parameters could be acquired using a combination of architectural typologies linked to crowdsourced methods that would sample neighborhoods. The goal is the creation of UCP data that reflect the unique form and function of individual cities and permits scalar variation to meet the needs of different models. As these form-based features of the imagery are digitized, all morphological form based UCPs can be computer generated and to any grid size (Fig. 5). Details are provided in the following sections.

3.2. The digital synthetic city (DSC) tool

Among other synthetic techniques (Aliaga et al., 2013), the DSC is a heuristic-based computer-assisted means of generating, from high-resolution satellite imagery, digital synthetic buildings that capture the essence of building dimensions and layout for cities with sufficient accuracy for many climate modeling applications. There are many techniques for creating 3D urban models of which

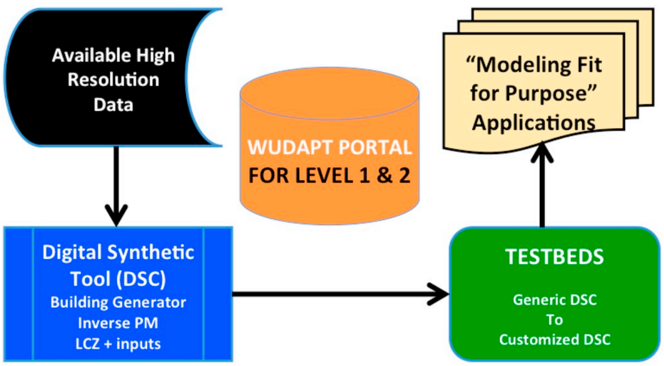

Fig. 4. Schematic: An overview of Level 1 and 2.

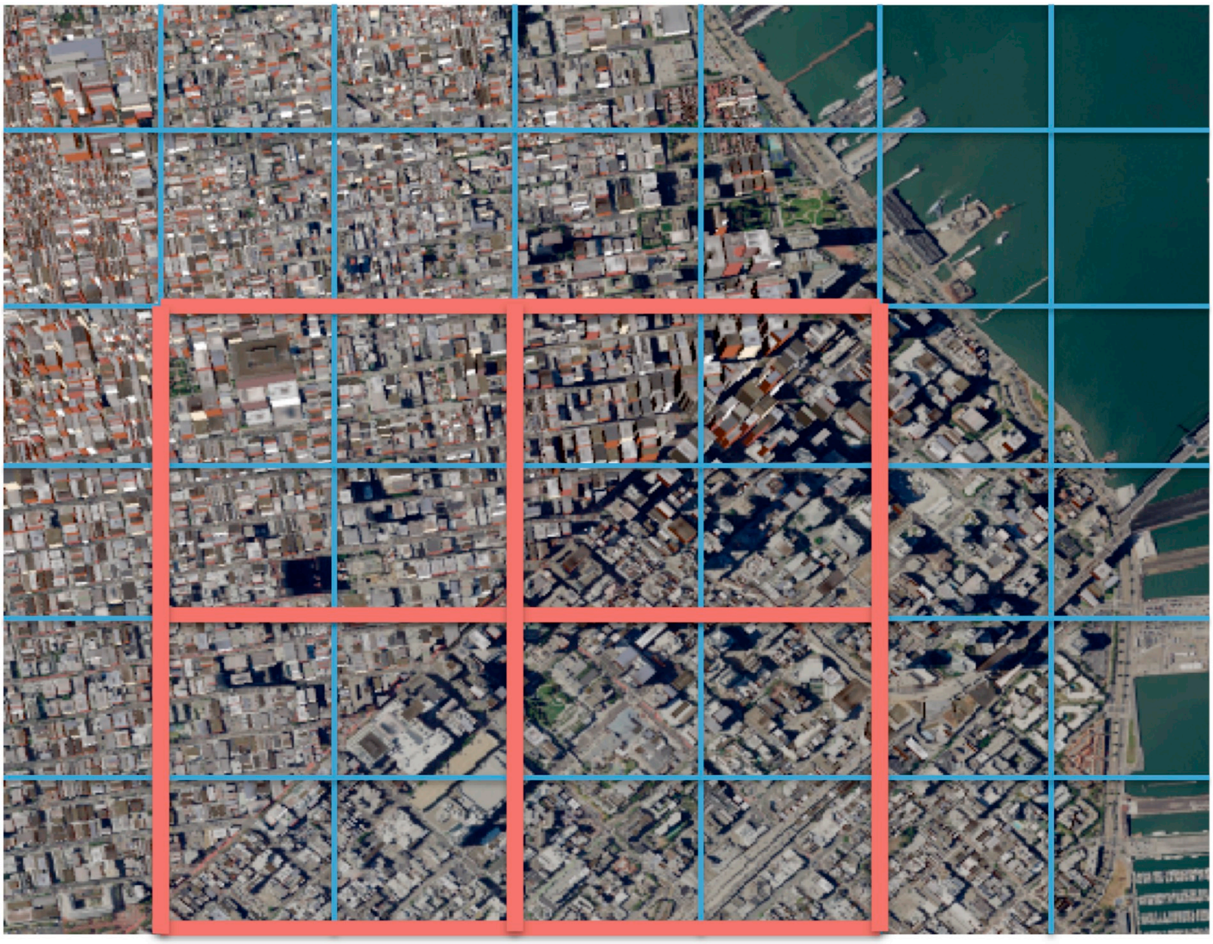

Fig. 5. Computing scale dependent Urban Canopy Parameters (UCP)s given digitized urban morphology from high-resolution satellite imagery. UCPs can be computed for each and every grid. Grid size is user choice.

procedural modeling (e.g., Garcia-Dorado et al., 2017; Vanegas et al., 2009a) and urban reconstruction (e.g., Musialski et al., 2013) are commonly used. Procedural modeling defines a set of rules and parameters to generate content and it has been successfully applied to urban spaces (e.g. Parish and Müller, 2001; Vanegas et al., 2009b; Vanegas et al., 2012a). The DSC automatically produces

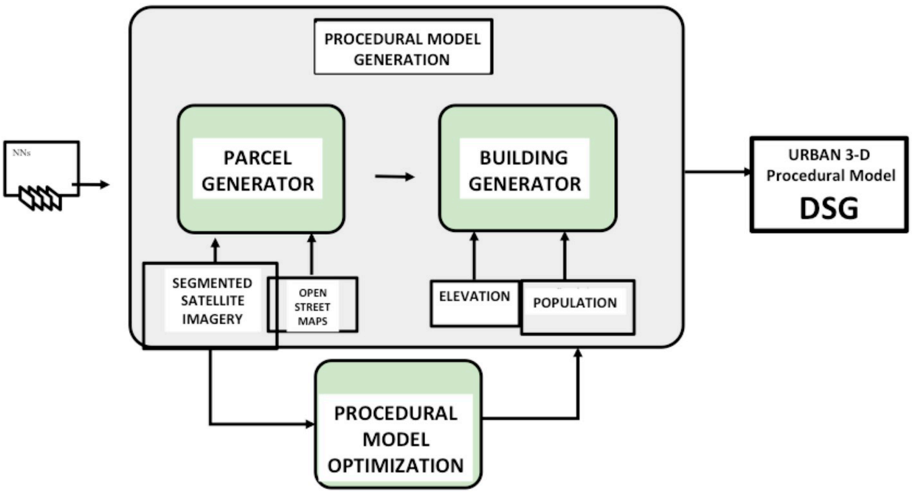

Fig. 6. Digital Synthetic City pipeline showing visual summary of the DSC workflow.

a 3D city model. At its core is an inverse procedural modeling algorithm (e.g., Vanegas et al., 2012b) that is fully automatic and produces a 3D approximation of an urban area from satellite imagery and global scale data that include a road network, population, and coarse elevation data (Fig 6 and 7). The DSC tool 'builds' the city by analyzing the data on parcels, buildings and their setbacks, population, and terrain elevation.

Briefly, the DSC's main steps are demonstrated in Fig. 6: procedural model generation component, parcel area estimation component, and procedural model optimization component. While a detailed formulation of the DSC framework, algorithm, and initial prototype are described in Aliaga et al. (2018, under review), we provide a summary.

- The *procedural model generation component* takes as input a geo-registered segmented and labeled satellite image and the corresponding geo-registered OSM road network. For the DSC, we assume the labels of building, ground cover, and roads in the satellite images. Individual city blocks are extracted from the satellite imagery and an initial geography of building parcels is created using the freely available geo registered global elevation JAXA dataset (30-m mesh, accuracy about 5 m) and ORNL's LANDSCAN Global Population Data (latest version is for 2016). The building generator computes for each parcel inside a synthetic city block, the building type, building height, and setback values, and subsequently the initial 3D building geometry. An appropriate building geometry is assigned based on the building's height and the setbacks associated with the building's type. To create a building geometry model, the generator uses both global-scale population and global-scale elevation data to compute the building type within each parcel. It also uses per-building-type triple typical setback ranges (front, rear, and side setback ranges) (Figure3b). Then, the elevation data, building type, and setback ranges are used to create an appropriately sized procedural building model. The estimated building height is scaled to the range [0, Hmax] where Hmax is, by default, the maximum building height of a typical city, or is a single number provided as input for a target urban area. Our method uses six procedural building types based on the LCZ classification. We use population data to estimate the density of a parcel. Thus, our six types are all combinations of low/mid/high rise with a dense/sparse component, i.e.: 1) Low Rise Sparse, 2) Low Rise Dense, 3) Mid Rise Sparse, 4) Mid Rise Dense, 5) High Rise Sparse, and 6) High Rise Dense. Further, we define a typical front, rear, and side setback range for each building type. To determine the building type $t_{i,j}$ for a parcel, we split the building height range into three percentiles corresponding to: Low Rise, Mid Rise, and High Rise Buildings. Using the population data of a parcel, we further split each percentile into two percentiles to define sparse vs. dense areas. The result is the classification scheme for the listed six building types. Finally, we compute an appropriate building geometry model based on the building's height and the setbacks associated with the building's type.

- The *parcel estimation component*, used during model generation, makes use of an analysis of the typical parcel sizes and building sizes in a city in order to train a neural network for robustly producing a set of parcel area networks. The neural network ingests the noisy and error-prone segmentation of a satellite image of a city block and produces crisp and reasonable parcel areas as output. Thus, our approach does not rely on a perfect satellite image segmentation but instead is able to cope with typical occlusions and misclassifications errors which in turn make the tool very robust in practice.
- The *procedural optimization component* iteratively executes the generation process to increase the similarity between the synthetically created building outlines and a small calibration dataset comprised of actual building footprint areas. By making use of the

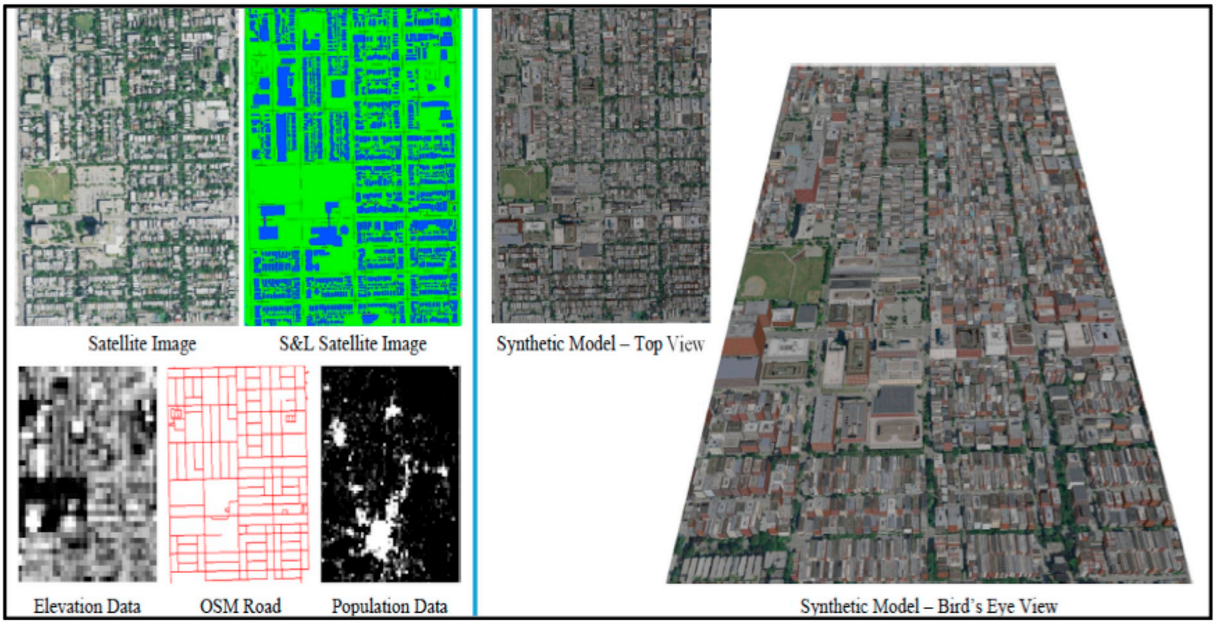

Fig. 7. Intermediate products of DSC processing

calibration dataset (e.g., a few percent of ground truth building footprint areas), the system parameters are tuned to produce a significant improvement in the overall accuracy in the end.

Altogether, the DSC tool can automatically generate a complete fully optimized 3D model of a city (with parcels, buildings, and roads) using just a satellite image and OSM in 5 min to two hours depending on the size of the urban area. The final procedural model output can be visually compared to Google Earth. For our multiple test cities, Fig. 8 compares various views of our 3D urban model to corresponding views obtained from Google Earth. Here we can see that from a distance, there is similitude. This similitude will diminish when individual buildings are considered.

Although the DSC has limitations (e.g. limited building types, block subdivisions, and accuracy), it is a very practical and expedient approach to create a digital urban landscape with similar physical properties to the actual city. In other words, the DSC captures the spatial heterogeneity of building geometry in cities and allows unique UCPs to be generated at appropriate model grid sizes. Moreover, it has the capacity to integrate other information (e.g. building materials and architectural features) to greatly enhance the product. For example, the DSC tool has two provisions: (1) the Building Type Refinement (BTR) to handle inputs of building properties such as albedo, heat capacities, and thermal admittances as probability distribution functions or other formats and (2) Partial Building Knowledge (PBK) to accommodate architectural variations based on additional data including materials. The BTR and PBK are being developed as either tools of the portal-based DSC or as part of downloadable software (Fig. 9. These tools of the DSC make it feasible and possible to customize (Section 3.3) to specific cities with data based on crowdsourcing Apps (CSAPPS) which will be implemented using the city-specific Testbeds described in Section 3.4.

Fig. 8. Example DSC outputs. Left column: Views of cities using Google Earth. Right column: Similar views using automatically generated procedural model from DSC. Top row, Chicago, Bottom row, San Francisco.

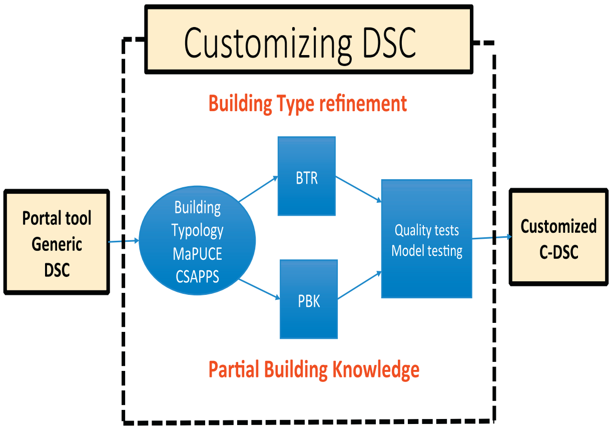

Fig. 9. Schematic: Tools to customize the DSC.

3.3. Enhancing DSC to generate building-scale parameters and properties

The acquisition of model relevant information on buildings (e.g., type and pattern of use, dimensions, roof shape, and material properties of the envelope) poses a major challenge for WUDAPT. Although many of the UCP parameters associated with building heights and layout can be obtained from the DSC, building information would provide UCP data on thermal and radiative properties (Table 1) and on anthropogenic heat flux. These data can be used to support modeling that links decision-making at the building scale to atmospheric outcomes.

Currently, the only global building database designed for climate modeling was developed by Jackson et al. (2010) using a 'top-down' approach. Thirty-three global regions with relatively homogeneous climate and housing characteristics were created and for each, thermal and radiative properties were assigned to four urban landscape types comprised of low, medium and high building densities and high-rise. This database distinguishes among urban classes but it has limited information on building use (e.g. residential, industrial and commercial), which regulates the timing and intensity of emissions. The WUDAPT approach is based on a pseudo 'bottom-up' approach, which relies on building archetypes (Fig. 10) that characterize the building stock in each city. The model for this approach is based on two related projects. TABULA developed national residential building typologies for 25 EU counties that consisted of: a classification according to age, size, etc.; a set of example buildings with typical energy consumption values and; associated information on building insulation and energy supply systems. The MAPUCE project used the French architectural database to extract generic building types based on dimensions, age, use and geographic area (Tornay et al., 2017). These types were then used to create urban surface cover and derive UCP values on roof and wall properties that included roof pitch and the

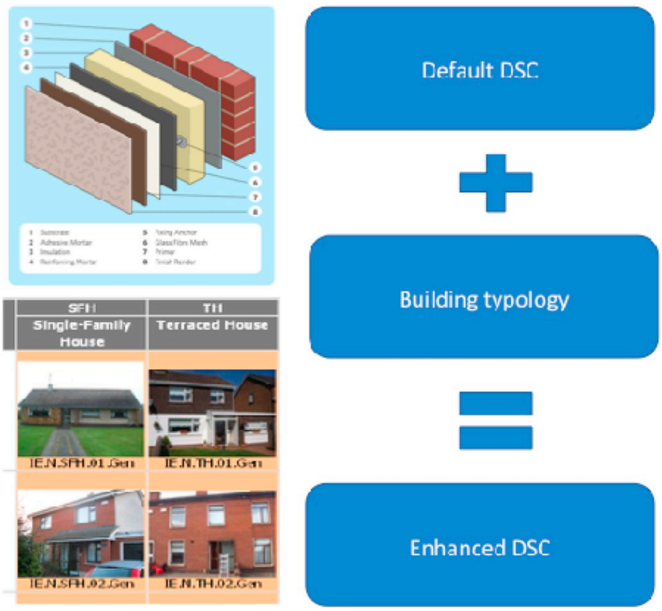

Fig. 10. Customizing the DSC based on building typology to generate information on Building material and properties.

material properties of facets and HVAC use. These data have been used in the Town Energy Budget (TEB) model that simulates building energy use in response to climate drivers and building properties.

The WUDAPT approach is still being designed but it will have three elements:

1. A building archetype database to capture the variation within and between cities at different scales (Fig. 11). The database will contain information on characteristic building use, date of construction, material, surface cover; glazed wall fraction, etc (Masson et al. 2017a,b).
2. A sampling methodology for gathering these data for a selected city. One approach would be to use the Level 0 (LCZ) map as a sampling frame however, different strategies may be appropriate for individual cities.
3. A process for linking building level data to the DSC. This would be based on a probabilistic assessment of the likely archetype associated with the simulated urban landscape based on matching similar shapes and heights, population data and LCZ type.

Creating the WUDAPT building archetype database relies on the expertise of architects from about two dozen countries,

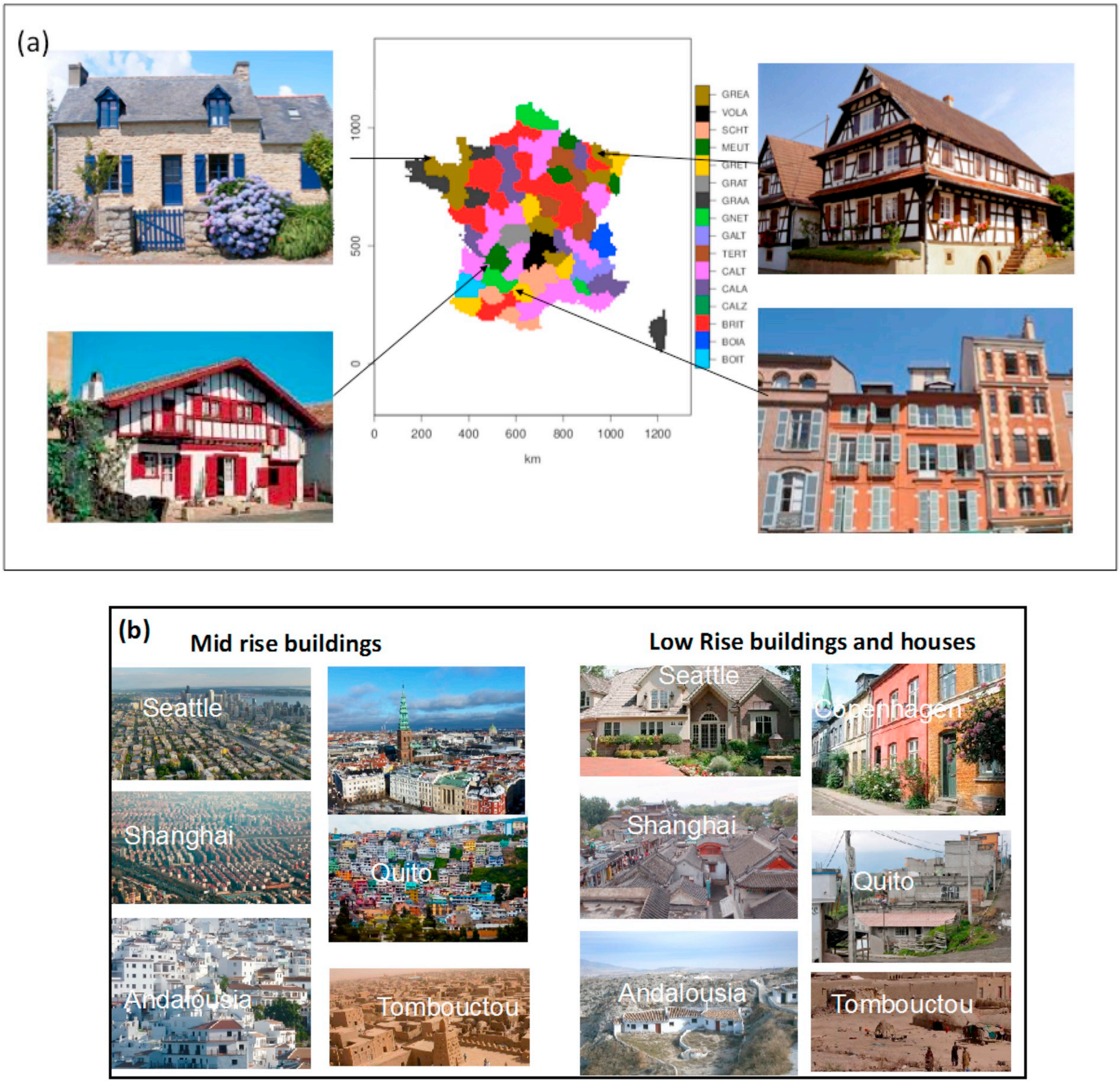

Fig. 11. (a) illustrating within country (France) variability of building's architecture for low buildings and houses built before 1948. Each color on the map corresponds to a typical building's architectures and wall/roof materials. (*source*: MAPUCE project (Masson et al., 2015)). (b) Illustration of worldwide variability of building's architecture for mid-rise buildings (6 pictures on the left) and low-rise buildings and houses (6 pictures on the right).

coordinated by the School of Architecture and Urbanism at the University of Sao Paolo, along with efforts being devised by each of the Testbeds. In developing the archetype database, WUDAPT will gather a library of geocoded images of the international building stock and rely on local experts to extract relevant properties. Each photo will be annotated with radiative and thermal properties using 'look-up' tables.

Acquiring the actual building data in each city will rely on a variety of methods including crowd-source applications that would be available on mobile phone platforms and permit classification into an archetype. Much of this infrastructure is still in development and will rely on the expertise of architects and the contribution of Testbed cities. The enhanced DSC would allow WUDAPT to generate UCP data on thermal/radiative properties and would provide the opportunity to link building energy demand (and indoor human comfort) to climate models. We envision that the Testbeds will be critical in testing and evaluating the efficacy of the approach outlined and improve it for wider application.

3.4. Design implementation approach utilizing city specific testbeds

The WMO Guide for Integrated Urban Services (WMO, 2018) recommends the concept of Testbeds for development, testing and evaluation of Urban Integrated Hydro-Meteorological, Climate and Environmental Services. A Testbed is a city that includes all essential information needed for providing Urban Integrated Services, as well as information on the measures taken as a result of the Services, on the behavior of people, on the target parameters, etc. (WMO, 2018). The purpose of a Testbed is to develop the models, perform diagnostic and statistical evaluation but most importantly, to co-design, co-develop and build relationships with partners. Testbeds with data from all fields relevant for the target parameters and variables (e.g., flooded area, soil water content, human behavior) are needed for model development, for diagnostic evaluation and quantitative user evaluation. These will need independent data sets for initialization, assimilation and evaluation to allow for robust testing and development.

WUDAPT will initially adopt a city-specific Testbeds prototype for "proof of concept" testing as the strategic approach, employing a heuristic, community-based means towards customization of the DSC, ensuring that each city and regions in the world will have their unique morphological structures, building construction materials and cultural features captured in the generation of UCPs (Fig. 10). For this, urban experts will discern their cities' unique features and provide samples of such features using crowdsourcing APPS and sampling approaches described above to collect and incorporate such data into the DSC. These Testbeds will typically already have a rich set of data as a basis and urban climate expertise. Each participating city would follow the essential steps listed below:

1. Create a DSC using the requisite high-resolution input satellite data, population and terrain elevation data. Evaluate the DSC by comparison with available baseline data such as 3D building models and against a unique set of Sky View Factor (SVF) data (Middel et al., 2018) described in the Appendix.
2. Access very high resolution Google type visual imagery, photographs from Google Street View and Mapillary, and where possible

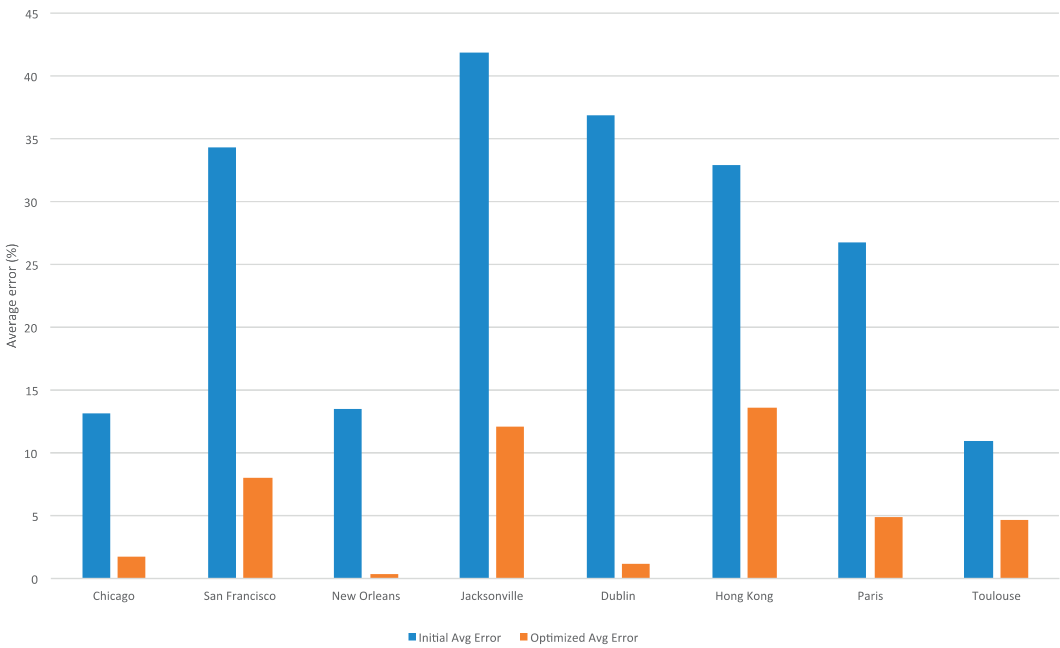

Fig. 12. Output Accuracy. We show the average of building footprint area error and building height error for several test cities using automatically produced DSC procedural output. The right column (orange) for each city is the output after the use of our procedural model optimization component.

data from OpenStreetMap (OSM).
3. Develop the CSAPP sampling strategy and deploy the CSAPPs to gather details on the buildings via the approach based on the Building Typology strategy.
4. Incorporate the CSAPP data into the DSC model to enrich the annotated Building Typology photo catalog.
5. Generate the UCPs from the C-DSC outputs.
6. Perform, assess and evaluate a wide variety of model applications (see table of model types) using the computed C-DSC-based UCP data to ensure usefulness and adequacy of the WUDAPT Level 1&2 data.
7. Prepare and codify the resulting UCP database and upload to the WUDAPT Portal.
8. Design and implement a QA plan.

The shared experience from these Testbeds from this stage will provide the bases for the protocols of the final recommended approach. As this is a portal-based approach, the results will become part of WUDAPT's global urban database and contribute to the dissemination of urban climate knowledge.

4. Results and discussion

At least a dozen Testbed cities (Table 4 in the Appendix) are currently engaged and others are being considered. Initial, albeit limited, results are described below to illustrate the current state of the methodology development.

4.1. Preliminary results of the DSC

Initial results from the use of the DSC tool to generate 3D models of several test cities shown earlier in Fig. 8) visually contrasts the

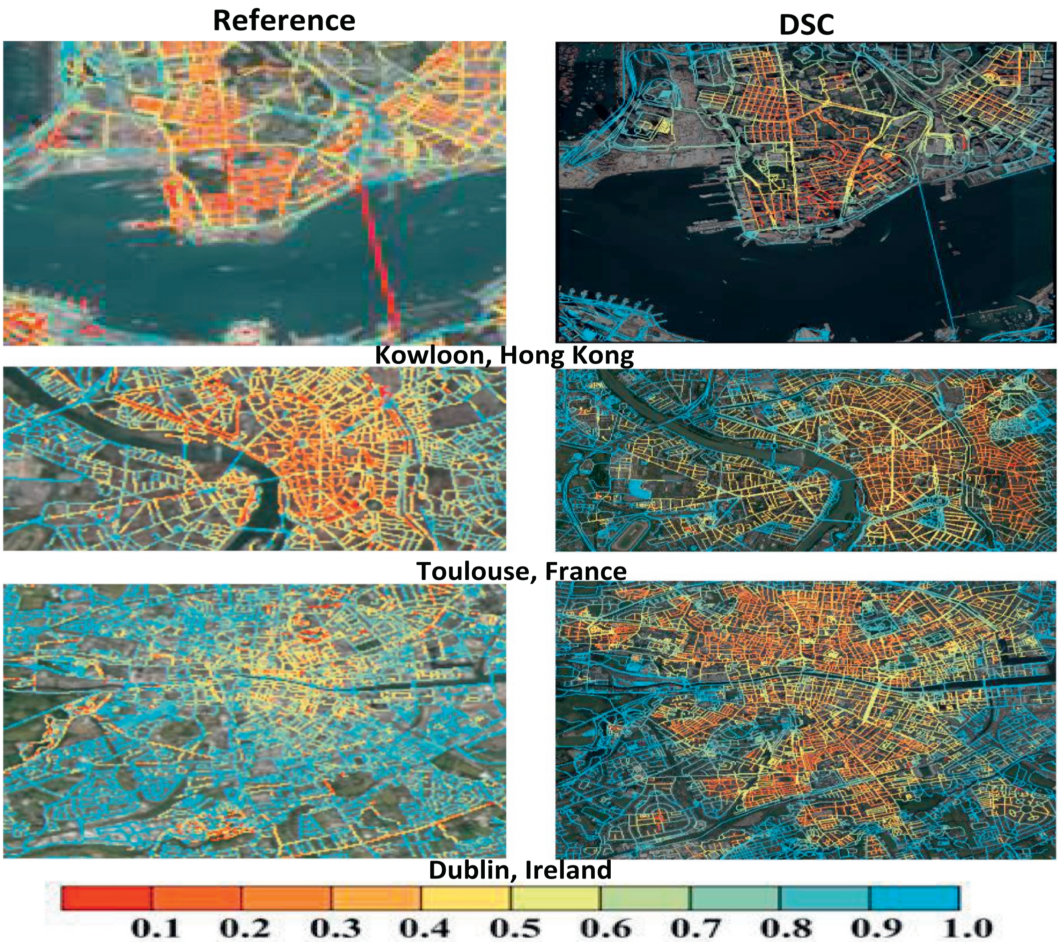

Fig. 13. Sky View Factors. Left: SVF computed using Middel et al., 2018 and Google Earth Street View images. Right: SVF computed using automatically generated procedural model from DSC. Some discrepancies are because DSC computes SVF for a denser set of roads and DSC does not compute SVF correctly over water bodies.

simulated and actual urban landscapes for comparison. From a distance, there is remarkable similitude, but a careful, close-in look will reveal differences, primarily with respect to details of individual building elements as anticipated. Fig. 12 compares DSC output with measured building height and footprint area for several cities around the world. Overall, the mean absolute error (MAE) is just 5.8%. We can anticipate this error to be reduced further as the planned additional data to customize the DSC is implemented. The optimized column is the result of using a sample (5–10%) of building footprint areas measured across the study area – these data are available for many cities or can be easily generated. Using the DSC, the SVF can be obtained in a straightforward manner by sampling sky visibility along the centerline of the road vectors. Fig. 13 compares the SVF values for Hong Kong, Toulouse, and Dublin computed using the automatic output of DSC to the method of Middel et al. (2018), which is based on an analysis of Google Street View images. While our results are not identical, they are similar enough to be used as a starting point for SVF usage.

As an example of UCP computation, we computed the area-weighted building height (A_h) and building surface plan area ratio (λ_b) for Hong Kong. The approximate 11 × 11 km test area of Hong Kong is divided into a grid of 110 × 115 cells, with each cell spanning 100 × 100 m. Within each cell an aggregated area weighted building height (A_h) is computed based on DSC values. Fig. 14 shows the result of using a Kolmogorov-Smirnov test (ks-test) to measure the similarity of the distribution of DSC-based A_h's values to ground truth. In particular, the horizontal axis represents into how many bins is the UCP value range divided. The vertical axis is the result of the ks-test and it measures the similarity of the distribution of DSC-based values to the distribution of ground truth values from the same bins. We highlight two typical significance value thresholds (i.e., $\alpha = 0.05$ and $\alpha = 0.01$). For example, the graph shows that for area-weighted building height DSC-based values yield a distribution of values similar to ground truth at a significance value of $\alpha = 0.05$ when using approximately 60 bins. The bin size in this case is 6.8 m which can be interpreted as an A_h accuracy of +/− 0.83% (i.e., 100/60 × 0.5). Similarly, for building surface plan area ratio, the ratios using DSC outputs vs ground truth are similar at a significance value of $\alpha = 0.05$ when using approximately 75 bins (i.e. a granularity of 0.18 or ± 0.67%). Hence, for reasonable cell and bin sizes, the automatically produced DSC output can be used to compute fairly accurate UCP values.

The DSC will be customized by adding local information. Fig. 15a shows raw output from generic DSC for the Kowloon Peninsula of Hong Kong. It can be seen that the building footprints are generally very well recognized, even if the exact shape of buildings may not match. For the whole domain, the error of building area detected is as low as 5%. Moreover, despite the relatively highly dense property, there is some vegetation cover existing in the urban area in Hong Kong (mainly parks or trees), which requires customization from local vegetation data to achieve verisimilitude. Another approach is to incorporate NDVI (Normalized Difference Vegetation Index) data to ensure that green areas are included in the DSC. Results of the customization of the DSC applying local vegetation data derived from Google satellite images are shown in Fig. 15b. Fig. 15c & 15d show scatter plots of results of raw DSC and customized DSC, which are gridded values at a 100 m resolution for two example UCPs (plan area ratio, λ_p, and area weighted building height, A_h) based on actual building data, respectively. The correlation coefficient is as high as 0.68 for λ_p and 0.54 for A_h, which indicates promising results from the C-DSC approach despite the heterogeneity of the Hong Kong landscape.

4.2. Current and ongoing testbed activities

4.2.1. This section describes current Testbed activities

1. Methods developments: The implementation and development of the customized DSC prototype tool capable of ingesting city-specific building material and the annotated building thermal and radiative properties of building matter from the geotagged

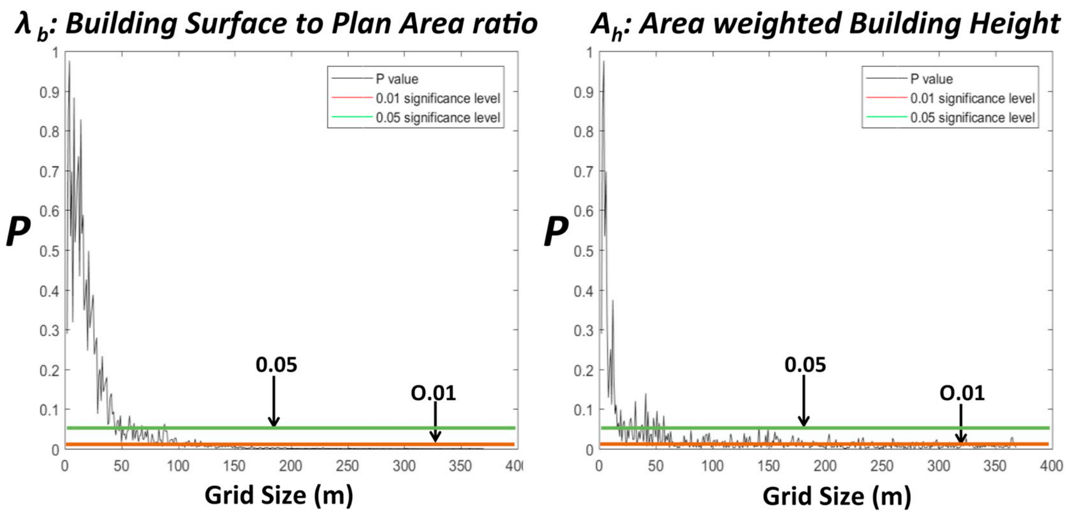

Fig. 14. Example UCP for Hong Kong. To quantify how accurate our DSC produced output can obtain typical UCP values, we analyze building surface-to-plan area ratio and area weighted buiding height. For both UCP types, the distribution of values is not statistically different than ground truth at either 0.05 or 0.01 significance values. (see text for more details).

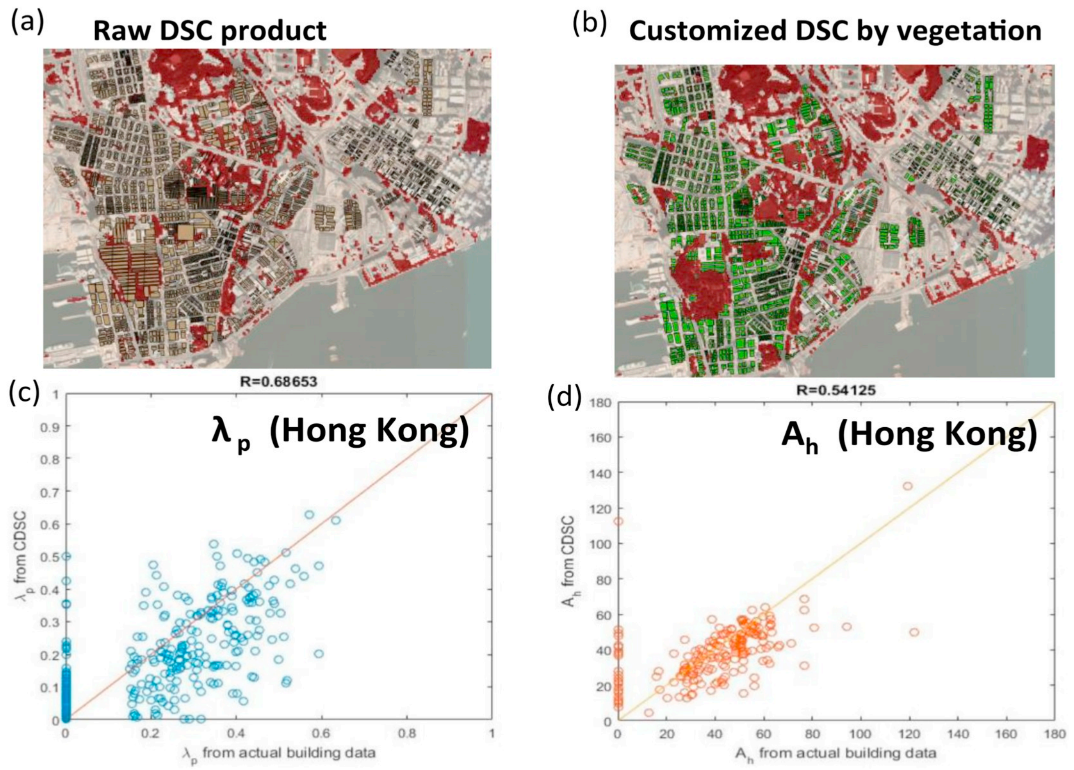

Fig. 15. Top: Customizing the DSC; using DSC tool to replace building in areas that are tree covered. a) Raw DSC product (yellow = building, red = vegetation), b) Customized DSC by vegetation data, Bottom: Scatter plot of (c) λ_p and (d) A_h derived from NUDAPT-type actual building data and DSC. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

photo-catalogues of building typology generated from the CSAPPS has been initiated and led by the Dublin Testbed (cf Section 2.3). Other Testbeds will then apply this C-DSC tool in their respective cities. Initial accuracy checks of the DSC based on the availability of actual building data for the entire city have been conducted for Hong Kong, Dublin, and Toulouse.

2. Initial model testing and applications using WRF; e.g., WRF modeling using bootstrapping approaches have begun. For Hong Kong and other cites of the Pearl River Delta (PRD), (Wong et al., 2018), studies of the historical evolution of urbanization in the PRD Region including Hong Kong using WUDAPT (Cai et al., 2018; Wang, 2018) and WRF modeling (Zhang et al. 2010a, Ren et al. 2017, Tse et al. 2018), linking WUDAPT to ENVI-met, development of urban climate maps (Xu et al., 2017) and development and deployment of real-time street-level air-quality models. At the outset, Testbeds for Chengdu, Guangzhou, Hong Kong, Beijing, Sao Paolo, Toulouse, and Hamburg will be engaged similarly, beginning with accuracy checks using actual data, each examining the efficacy of various crowdsourcing approaches to generating the inputs for customizing the DSCs and examining and assessing tradeoff issues between the C-DSC accuracy as a function of grid size (see next section). They will be engaged in a variety of model testing activities, evaluating the use of C-DSC UCP outcomes. A wide variety of modeling studies under consideration will be useful for determining the efficacy of C-DSC generated UCPs. Model testing and applications including using WRF, CMAQ, ENVI-met and LES techniques focusing on the use of advanced LCZ-based UCPs (WUDAPT Level 1) are planned (See Appendix and Fig. 18). There is the potential for exploring using the C-DSC as a platform for fine grid model applications for street level air quality exposure modeling (Shi et al., 2018) and Street-in-Grid air quality modeling; e.g., Kim et al. (2018), and one such study has already begun for Guangzhou (Wu and Wang, 2018). We seek to engage these Testbeds and to invite others around the world to ensure broad world experience and consistency in the C-DSC, and to begin initial linkages to the Urban Multi-scale Environmental Predictor (UMEP) system (Lindberg et al. 2017, 2018). A strategic effort to map, generate and analyze GHG emissions is the focus of the Tokyo Testbed. We anticipate efforts to extending this Testbed's current capability with the WUDAPT LCZ approach to perform enhanced temporal and spatial carbon mapping and characterizations in WUDAPT using the WUDAPT DSC framework and CSAPP sampling (Table A.2).

4.3. Storing and transmitting UCPs

Following the approach of NUDAPT, WUDAPT L1/L2 processes will generate unique UCPs for each model grid cell (Table 1). The implication is that each grid can have a distinct effect on model simulations of airflow, radiation exchanges, the turbulence energy budget, pollutant deposition velocity, etc. It is possible and useful to describe the WUDAPT output for a city using a unique combination of key UCPs; this data string is akin to an urban DNA code (Fig. 16) and coded either in bar or QR code (for maximum

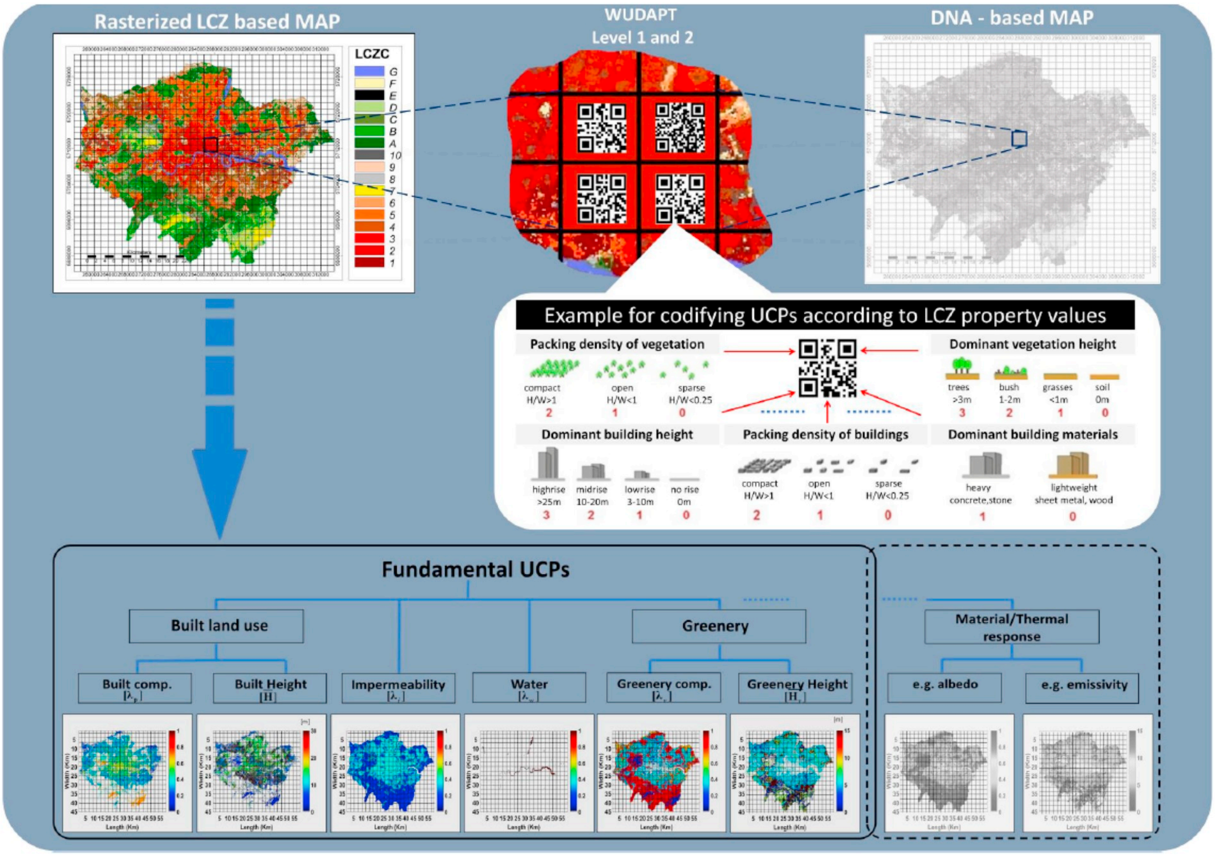

Fig. 16. Schematic showing DNA-like coding for UCP from WUDAPT 1&2.

resolution) as shown in the figure. WUDAPT intends to produce a protocol for coding UCP data to provide model applications with fit-for-purpose data appropriate to the project. The DSC is capable of generating form based UCPs according to any user specified grid raster size. The utility of formatting (codifying) the data may provide a means for examining and studying the UCP set as DNA for such considerations as to the UCP-related factors that make a city more sustainable or resilient, providing urban planners with a tool for optimizing sustainability and resiliency. For a simplified code, we can start with each UCP such as was utilized to generate the LCZs. Each value in the code sequence of UCPs could represent a preselected range of values shown in Fig. 16 as suggested by Stewart and Oke (2012). Alternatively, we could further discretize to decile values such as binning from 1 to 10 with bins of different decile ranges assigned an ordinate value 0–9 as shown in Fig. 16.

At this point, it is also important to bear in mind that for numerical modeling of urban thermal fluid dynamics for a range of weather and climate applications, UCPs should be appropriately defined and derived for the corresponding scale (and therefore nature) of the application considered. This is illustrated schematically in the bottom row of Fig. 16. The Level 0 map is extracted in rasterized form into a gridded format. The 17 classes used in the LCZ mapping (as per Stewart and Oke, 2012) are decoded and summarized into 6 two-dimensional (2-D) pixelated data sets of the fundamental, independent UCPs. These are considered the fundamental parameters, in the sense that all the 17 classes in the standard LCZ mapping can be reproduced as a combination of these 6 fundamental parameters (Mouzourides et al., 2018). The decoding into fundamental UCPs at the Level 0 (after the initial extraction in gridded format) is required in order to enable the deduction of the corresponding quantitative values of the fundamental UCPs (and thereby more composite UCPs) later on at the appropriate scale or cell size required for the application, based on rigorous methodologies (Mouzourides et al. 2013, 2014, 2017).

There are underlying issues to be worked out to implement these innovations towards accommodating the wide range of urban-centric type applications. In practice, the "coded DNA" set we propose here is inherently scale dependent. First, it is well recognized that there is no "universal, one-size fits all grid size". Second, especially for microscale modeling, the accuracy of UCPs from the C-DSC system will diminish with decreasing grid size. The level of acceptable accuracy by grid size is an outcome to be investigated in this "Work in Progress" stage and established, knowing that one can aggregate the coding to larger grid sizes. Additionally, studies will be undertaken to characterize UCPs in more fundamental contexts (a) consistent with the Stewart and Oke (2012) LCZ paradigm and (b) similar to "the chromosome category" in the DNA analogy characterized by representative subsets of other UCPs or urban indicators consistent with Fig. 16. This can set the stage for the development of a scale dependent coding protocol by the WUDAPT community.

Finally, information in Table 1 on building typologies will require building scale information to be generated by means outlined in Section 3.3. Here tools such as LZW compression might serve as an efficient means to convey this type information. This can then be decompressed for model or analyses applications.

4.4. Summary and path-forward activities

We propose a strategic and practical means to generate urban canopy data at WUDAPT Level 1 and 2 using a portal-based customized C-DSC tool. The data for the customization will be facilitated by applying the MaPUCE and crowdsourcing paradigms implemented by ad hoc activities of urban experts in their respective urban Testbeds currently being established and now underway. The recommendations based on the synthesizing of the experience and best practice from these Testbeds will constitute the final methodology protocol. The coverage of Testbeds will be worldwide to adequately represent regional variations. They each have specific guidance but yet sufficient flexibility to encourage diverse utility of the database. In addition, given that the useable lifetime of morphological structures spans at least 2 generations, it is of strategic benefit that WUDAPT is available for design and urban planning and other uses by the urban community, setting a two to three year horizon, and a rollout of the prototype at the next triennial IAUC conference, which seems to be a reasonable timeframe. Also noteworthy, WUDAPT Level 1 and 2 data can be created at regular intervals going backward in time, permitting the development of a consistent time series and analysis of urbanization of any cities or regions on earth. Based on the extracted and developed historical urban morphological information, future land use patterns can be predicted as a reference for local planners and government officials especially for those in developing countries and regions under fast urbanization but which lack urban data. This developed data can also allow climatologists to run complex climate models to gauge the impact of urbanization on climate at local, city, and regional scales. The modeled results, when properly formatted and presented, may allow policy makers and industry stakeholders to draw up climate maps for their cities so as to guide better city planning decision making at various design scales (Ng and Ren, 2015; Ren et al., 2017). The WUDAPT Portal will provide the platform for hosting the UCP outputs, as multiscale codified gridded sets. Moreover, the Portal, as infrastructure, will host tools derived during Testbed modeling activities to promote the utility of the database.

Already, informal interests have been expressed by organizations including Passive Low Energy Architecture (PLEA), the International Association for Urban Climate, (IAUC), and the World Meteorological Organization (WMO), to engage in the development and implementation. Given the overriding principle of WUDAPT to be community-based, the development and implementation activities are open and unrestricted to the world community, self-regulating, and on a volunteer base. Thus, participation in any and all activities leading to full implementation and eventual utilization is encouraged and facilitated by all interested parties and communities around the world.

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Appendix A. Appendix

A.1. Sky view factor database in WUDAPT portal

In addition to likely availability of baseline building data, these Testbeds will benefit from a unique SVF database (60 cities currently processed through Jan 2019) shown in Table A.1 and now being made available on the WUDAPT portal based on the efforts and methodology described in Middel et al., 2018. These SVF datasets are developed using image-based 'big data' methods which can automatically calculate SVFs from Google Street View (GSV). GSV images in cities are acquired every 5–20 m on the street network and can provide a detailed sample of the urban landscape. The method projects acquired image cubes into hemispheric fisheye photos, the sky is detected using a modified Sobel filter and a flood-fill algorithm (Sobel and Feldman, 1968; Lindberg et al., 2017, 2018), and the SVF is calculated using a modified Steyn method (Middel et al., 2017). The SVF can be linked to both daytime radiation receipt at walls and street surfaces and nighttime radiation losses; for example, it is an important regulator of the magnitude of the urban heat island. Although natural areas, parks, backyards, etc. are under-sampled, comparisons with WUDAPT L0 data (Wang et al., 2018a, 2018b; Middel et al., 2018; Bechtel et al., 2017a, 2017b) show good agreement with urban LCZ parameter ranges. Moreover, this method can be expanded to extract information on trees, impervious surfaces, etc. within the urban canopy layer (Middel et al., 2019; Gong et al., 2018). SVF data generated by this method are available for a growing number of cities around the world in WUDAPT (Table A.1); apart from their intrinsic value, (and planned use in C-DSC) these data will also provide a valuable urban resource for testing other data products.

Table A.1
Processing status of SVF calculations for cities around the globe.
(Courtesy Middel 2019)

Urban area	Country	# of GSV Locations	SVF (average)
Atlanta, GA	US	541,962	0.689
Baltimore, MD	US	523,709	0.786
Bangkok	TH	1,779,185	0.764
Barcelona	ES	602,645	0.709
Be'er Sheva	IL	57,608	0.898
Belgrade	RS	346,661	0.807
Bogotá	CO	694,329	0.776
Bonn	DE	93,188	0.746
Boston	US	466,158	0.705
Brussels	BE	285,059	0.698
Bucharest	RO	321,145	0.777
Buffalo, NY	US	349,676	0.824
Cleveland, OH	US	352,365	0.757
Denver, CO	US	1,109,871	0.879
Dubai	IE	609,301	0.921
Dublin	IE	427,071	0.835
El Paso, TX	US	827,718	0.962
Frankfurt	DE	83,573	0.738
Fresno, CA	US	499,908	0.906
Ghent	BE	271,079	0.821
Gothenburg	SE	171,691	0.825
Hamburg	DE	253,958	0.702
Hong Kong	HK	625,136	0.548
Istanbul	TR	1,629,574	0.714
Johannesburg	AF	472,900	0.804
Kampala	UG	145,989	0.873
Kiev	RU	450,163	0.764
Kuala Lumpur	MY	429,877	0.720
Las Vegas, NV	US	1,073,711	0.938
London	UK	2,396,172	0.774
Los Angeles metro area, CA	US	9,354,005	0.889
Lyon	FR	179,821	0.682
Madrid	ES	827,932	0.751
Manhattan, NY	US	143,183	0.545
Miami, FL	US	1,005,440	0.835
Nantes	FR	203,440	0.812
New Orleans, LA	US	631,122	0.846
Orlando, FL	US	872,359	0.809
Paris	FR	304,823	0.586
Philadelphia, PA	US	936,231	0.723
Phoenix metro area, AZ	US	3,124,529	0.954
Richmond, VA	US	318,243	0.702
Rome	IT	700,481	0.739
Salt Lake City, UT	US	689,701	0.907
San Antonio, TX	US	1,117,303	0.904
San Francisco, CA	US	233,281	0.797
San Jose, CA	US	771,094	0.840
São Paolo	BR	2,559,340	0.787
Seoul	KR	613,971	0.68
Singapore	SG	948,674	0.685
Sofia	BG	311,971	0.786
Tampa, FL	US	693,181	0.772
Tel Aviv	IL	156,353	0.763
Tokyo	JP	3,736,082	0.693
Toulouse	FR	368,855	0.836
Tucson, AZ	US	565,825	0.956
Vancouver, BC	CA	693,193	0.781
Victoria, BC	CA	152,985	0.761
Warsaw	PL	601,920	0.755
Washington, DC	US	516,448	0.705
		60,604,277	

A.2. Current set of Testbeds

Table A.2
Current list of active Testbeds in different regions and continents and their likely modeling emphases. Tentative Testbeds are indicated (T).

Asia	Africa, Mid East	Europe	Americas	Other regions
Bangalore M	Dakar M	Dublin M, U	NYC M, L, U	Moscow (T)
Beijing M	Kampala M	Hamburg M	Sao Paolo M,A, E	Melbourne (T)
Chengdu E, M	Cairo (T)	Madrid M,	Phoenix H	Nanjing (T)
Guangzhou M, S, A	Jeddah	Paris M, S,	San Francisco (T)	Seoul (T)
Hong Kong M, E, A	Tel Aviv (T)	Toulouse M,	Victoria (T)	
Shanghai (T) M		Vienna (T) U	Toronto (T)	
Taipei M, A		London (T)	Minas Gerais (T)	
Tokyo G			Medellin (T)	
Mumbai (T)			Santiago (T)	
New Delhi (T)			Lima (T)	
Bhubaneshwar/Roukela				
Pune				
Trivandrum				
Ahmedabad				
Banaras				

Modeling and other applications keys for confirmed cities,
(M) Mesoscale, e.g., WRF or.
(E) Link to ENVIMet.
(S) Link to Street in Grid.
(U) Link to UMEP.
(A) Urban air quality.
(L) Link to LES, CFD.
(G) Greenhouse Gas.
(H) Urban Health.
(T) Tentative.

A.3. Brief Summary of Examples of current modeling systems to be utilized in W1&2 Testbeds modeling studies

A.3.1. Urbanized WRF

WUDAPT provides model parameter inputs to environmental models such as the WRF so as to be able to study and perform surface energy budget, weather, climate and air quality model applications for urban areas and anywhere in the world in consistent manner. A tool W2W (www.wudapt.org) has been developed and in the WUDAPT Portal linking the outputs of WUDAPT Level 0 into an urbanized version of a modeling system called “Weather Research and Forecasting” or WRF. WRF (Skamarock et al., 2008) is a community and science-based atmospheric modeling system in widespread use (currently ~ 20,000 code downloads) throughout the world. The W2W tool provides prospective users, the information and detailed instructions to enable the running of both urban canopy multi-layer versions in WRF (BEP by Martialli et al., 2002, and BEP-BEM Salamanca et al. (2009) and by using the accompanying form and function data tables of WUDAPT level “0” data based on the Local Climate Zone (LCZ) classification scheme by Stewart and Oke (2012). Fig. 17 is a summary of the methodology; an initial implementation for Madrid is in Brousse et al. (2016). Testbeds will modify and test the current W2W tool for linking the Level 1 and 2 database to running and applying urbanized WRF. This allows model application extensions to air quality simulations in systems such as WRF-Chem or WRF-CMAQ.

A.3.2. ENVI-met

ENVI-met is a prognostic, three-dimensional, high-resolution microclimate model. With its physical fundamentals that are based on the principles of fluid mechanics, thermodynamics and the laws of atmospheric physics it is able to calculate three-dimensional wind fields, turbulence, air temperature and humidity, radiative fluxes and pollutant dispersion (Bruse and Fleer, 1998). Microclimate models such as ENVI-met have the advantage that, thanks to their high spatial resolution, little parameterization is needed to represent objects of the urban environment: Trees, building materials, and complex structures can be directly reproduced within the model. The ENVI-met model has been evaluated and applied in many studies assessing the urban microclimate in various climatic regions (Nikolova et al., 2011; Yang et al., 2012; Simon, 2015) and has been previously used to assess LCZs in urban areas (Middel et al., 2014; Middel et al., 2015).

A current version of the portal tool WUDAPT2ENVI-met uses WUDAPT Level 0 data to generate model areas for the high-resolution microclimate model ENVI-met. It links level 0 data with the high resolution model thus offering a fast and easy way to digitize large urban areas in a worldwide consistent manner, the differences in spatial resolution generate issues (Fig. 18) Using higher level data featuring a city's unique morphologies including the geometry, variations and spatial distribution of buildings, architectural features, construction materials and green and pervious surfaces actual building as well as vegetation, the linkage between WUDAPT and ENVI-met offers a huge potential to simulate the urban microclimate in great detail. The combination of WUDAPT's DSC tool with ENVI-met should allow to analyze, develop and quantify different urban heat island mitigation strategies in

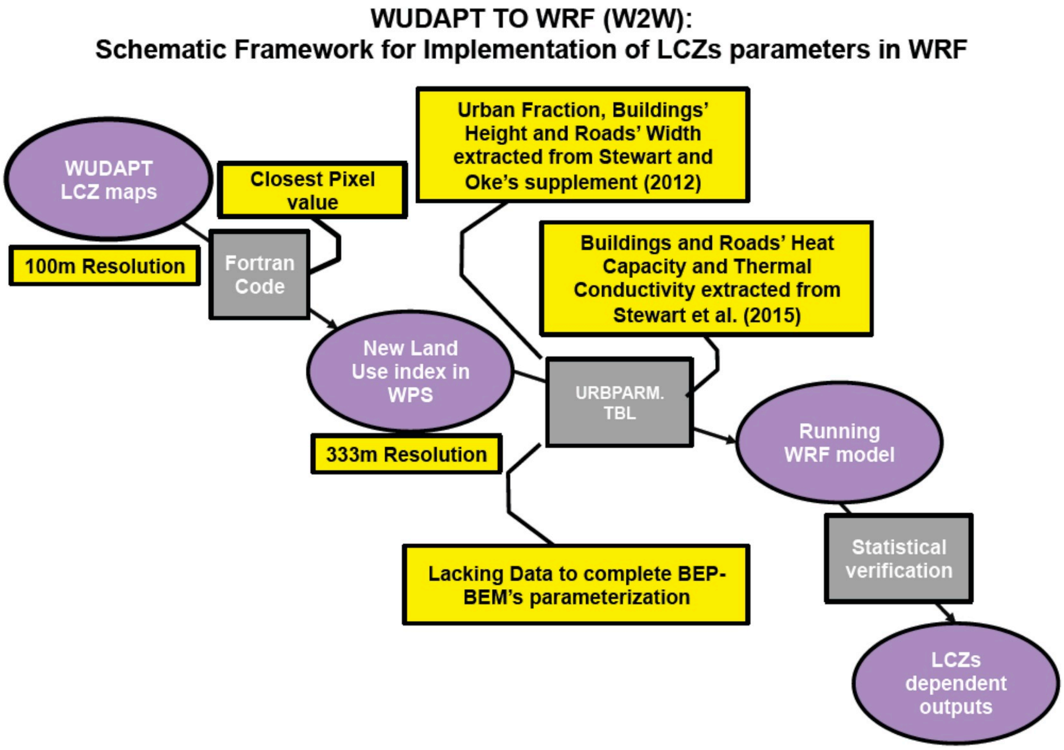

Fig. 17. Scheme for using WUDAPT Level 0 (W2W) in multi-layer urban canopy versions of WRF Based on Brousse et al. (2016).

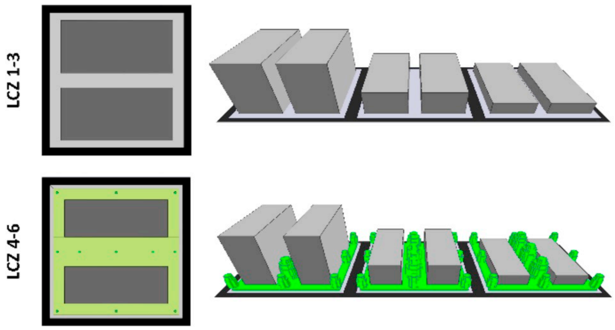

Fig. 18. Representation of the Standard LCZ tiles 1–3 and 4–6 gridded in 1 m resolution (they differ in building height only).

a fast and comparable way.

A.3.3. W12 and the urban multi-scale environmental predictor (UMEP)

Based on the UMEP workshop description on the ICUC10 website link: Exploring urban planning strategies and their effect on mitigating heat waves - examples from New York City https://www.ametsoc.org/index.cfm/ams/meetings-events/ams-meetings/10th-international-conference-on-urban-climate-14th-symposium-on-the-urban-environment/practical-workshop-the-urban-multi-scale-environmental-predictor-umep/

"UMEP is a versatile open source climate services tool for researchers, architects, urban planners, climatologists, and meteorologists, which can be used for a variety of applications related to outdoor thermal comfort, urban energy consumption, climate change mitigation (Lindberg et al., 2017, 2018). UMEP is developed as a plugin for QGIS a cross-platform, a free and open source desktop geographic information system (GIS) application. UMEP consists of a coupled modeling system which combines state-of-the-art 1-D and 2-D models with systems to input data from multiple sources, formats and at different temporal and spatial scales, and to generate output as data, graphs and maps. The tool also includes capabilities to connection to various databases such as WUDAPT (spatial) and WATCH (meteorology)"

Given such ongoing links, the W12 Testbeds will actively collaborate with the developers of the UMEP tool engaging in efforts to enhance the links to WUDAPT Level 1 and 2 database likely via the WIUDAPT Portal system.

A.3.4. Street–in-Grid (SinG) modeling studies

Studies and models at urban to local street level air pollution, climate change, and their impacts on population exposure and human health are becoming of increased interest and attention. Several state-of-the-science models have been recently developed for urban/local street-level air pollution modeling. The innovative modeling framework "SinG" (Kim et al., 2018) has recently be developed. The SinG system incorporates the street-network "Model of Urban Network of Intersecting Canyons and Highways" (or MUNICH) and the 3-D Eulerian chemical-transport model (CTM), Polair3D. Both models aim to incorporate detailed representations of gas-phase chemistry and secondary aerosol formation pathways. The WUDAPT Testbeds will be engaged with the SinG to develop linkages especially between the MUNICH system and the UCPs generated by the WUDAPT DSC tool.

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