HIGH-RESOLUTION AIR TEMPERATURE MAPPING IN URBAN AREAS
A Review on Different Modelling Techniques

by

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In this study, the importance of air temperature from different aspects (e. g., human and plant health, ecological and environmental processes, urban planning, and modelling) is presented in detail, and the major factors affecting air temperature in urban areas are introduced. Given the importance of air temperature, and the necessity of developing high-resolution spatio-temporal air-temperature maps, this paper categorizes the existing approaches for air temperature estimation into three categories (interpolation, regression, and simulation approaches) and reviews them. This paper focuses on high-resolution air temperature mapping in urban areas, which is difficult due to strong spatio-temporal variations. Different air temperature mapping approaches have been applied to an urban area (Berlin, Germany) and the results are presented and discussed. This review paper presents the advantages, limitations, and shortcomings of each approach in its original form. In addition, the feasibility of utilizing each approach for air temperature modelling in urban areas was investigated. Studies into the elimination of the limitations and shortcomings of each approach are presented, and the potential of developed techniques to address each limitation is discussed. Based upon previous studies and developments, the interpolation, regression and coupled simulation techniques show potential for spatio-temporal modelling of air temperature in urban areas. However, some of the shortcomings and limitations for development of high-resolution spatio-temporal maps in urban areas have not been properly addressed yet. Hence, some further studies into the elimination of remaining limitations, and improvement of current approaches to high-resolution spatio-temporal mapping of air temperature, are introduced as future research opportunities.

Key words: *air temperature, urban areas, spatio-temporal modelling techniques, high-resolution mapping*

Introduction

Temperature of the air (thermodynamic temperature or kinetic temperature) measured at a height of 2 meters above the land surface by an in situ thermometer (2-m air temperature), also called surface air temperature or, more accurately, air temperature at shelter height [1], is hereinafter named *air temperature*.

Air temperature is an essential component of the terrestrial environment conditions all over the world, and is involved in many important ecological processes (*e. g.*, actual and poten-

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tial evapotranspiration, net radiation or species distribution) [2-9], aerosol scattering coefficient [10], atmospheric boundary layer [11, 12], remote sensing processes (*e. g.*, atmospheric correction algorithms for the estimation of land surface temperature (LST) [13], land surface energy balance [14], the generation of several crop stress indices (*e. g.*, stress degree day or crop water stress index) [15, 16], and thermal indices (*e. g.*, physiological equivalent temperature, PET) [17-22]. Hence, the air temperature is required as an input variable for the calculation of these processes and indices, and it is very difficult to identify these processes and indices properly without fine-scale, continuous temperature monitoring [14]. Furthermore, accurate air temperature is needed to decrease the error of numerical models when air temperature is an important input parameter of a model [23].

Scientists believe that air temperature can influence both human and plant health. Air temperature is also an important parameter in the modelling of some diseases, and extreme temperature has a role on mortality. In 2010, about 216 million persons had malaria and World Health Organization [24] estimated more than 655000 deaths by malaria in the world. Studies have shown that there is a link between air temperature and malaria and have determined the relation between air temperature and malaria transmission (*e. g.*, [25-28]). Low temperature during the growing season causes stress, which may lead to lethal damage of tissue or whole tree seedlings [29-31]. Also the knowledge of the spatial variability of air temperature is needed for the efficient implementation of frost protection and the evaluation of the risk of frost [32, 33].

The population of the world that is living in urban areas is increasing. In 1950, around 29% of the global population was living in urban areas. This proportion had grown to 47% by the year 2000, and it is predicted that this proportion will grow to 69% by the year 2050 [34]. Thus, urban areas are continuously growing [35] and the number of people exposed to air temperature impact is expected to increase [36]. In western societies, the combined effects of growing urbanization and demographic change (*e. g.*, population aging) increase the risk of heat stress and mortality rates [37-40]. The relation between elevated air temperature and mortality has been reviewed by Basu and Samet [41]. The studies on the effects of elevated air temperature on the increase of mortality in Europe due to 2003 heat waves showed excess deaths in the different urban areas in different countries such as France [42], Spain [43], Italy [44], England and Wales [45], the Netherlands [46], and Switzerland [47]. Most studies on the relationship between the air temperature and mortality have shown that elder people are greatly affected by the increase in temperature, because the ability of their bodies for thermoregulation has decreased [48, 49]. Children are another sensitive group to air temperature [50], because their bodies do not have sufficient thermoregulation capacity [51]. Another disadvantage of growing urbanization is population density, which increases the exposure level and thus the vulnerability to heat stress [52-55]. Elevated air temperature in urban areas influences the atmospheric boundary layer dynamic [56], which is important for investigation of the GHG [57] and it also can influence the CO_2 diurnal cycle [58]. In addition, elevated air temperature in urban areas generated by the urban landscapes can influence the comfort and health of inhabitants as well as energy consumption and air quality [59-61]. Therefore, it is very important for urban planners to determine the effects of different land uses on air temperature and the spatial distribution pattern of air temperature is a suitable tool for evaluation of the correlation between air temperature and land uses and/or urban structures [60, 62].

Although, high-resolution data of air temperature is a pre-requisite for any approach towards the mitigation of elevated air temperature in urban areas [63, 64] and it is very important for urban planning and local climate investigation [60, 64], it has very high spatio-temporal variations and complicated calculation [65]. The thermal properties of urban elements have significant spatial variations [65] and spatio-temporal variations of air temperature in different cities are not similar [66]. For example, radiation absorption can highly influence daytime elevated air temperature in equatorial climate in calm and clear sky conditions. However, anthropogenic heat release can be a factor of night-time elevated air temperature in high-rise and dense metropolitan areas in cloudy conditions [66]. Hence, standard meteorological measurements, even supplemented by special-purpose measurements often prove insufficient to describe the high spatial variability of air temperature in urban areas [67] and it is necessary to estimate the high-resolution spatio-temporal air temperature maps in urban areas [68]. If so, these high-resolution estimations will be extremely useful for urban planning, building design, efficient design, and operation of urban infrastructures (*e. g.*, energy systems), and human thermal comfort [66, 69]. However, spatio-temporal air temperature mapping in urban areas is a complicated task, because there are too many factors that influence air temperature in urban areas. The major factors, which affect air temperature, can be categorized in three groups:

(1) Temporal effect variables, such as LST [4, 70-76], wind speed [77-82], and cloud cover [79, 82-85].
(2) Permanent effect variables (Spatial variables), such as land use/land cover [35, 63, 86-97], urban morphology [98-103], and building material and albedo [78, 98, 104-108].
(3) Cyclic effect variables, such as solar radiation [78, 106, 109, 110] and anthropogenic heat [111-117].

Based on our knowledge, a review on the different approaches of air temperature estimation in urban areas with emphasize on high-resolution mapping has not been performed. Given the importance of the air temperature and development of high-resolution spatio-temporal air-temperature maps (spatial resolution: less than 100 m, temporal resolution: one hour), this paper classifies the existing approaches for the air temperature estimation to three categories (interpolation, regression, and simulation approaches) and reviews them. The limitations and shortcomings of each approach are also outlined. In this paper, it is emphasized on the high-resolution air temperature mapping in the urban areas, which is difficult due to the strong temperature gradients. In addition, the different air temperature mapping approaches have been applied on an urban area (Berlin, Germany) and the results have been presented and discussed.

Air temperature mapping techniques

Interpolation techniques

The interpolation techniques are well-known as the simplest approach for air temperature distribution modelling. The source datasets for interpolation techniques are the temperature observations in the automatic meteorological stations and the non-static manual observations. Myers [118] reviews the basic statistical methodologies that are the base of most interpolation techniques. The general interpolation function is expressed:

$$T_a = f\left(x, y\right) \tag{1}$$

where x and y are the longitude and latitude, respectively, and f is the interpolation function that determines the relation between air temperature, T_a, and the location (x and y). There are a number of deterministic and geostatistical interpolation functions and they are ranged from the relatively simple nearest point method to more complex techniques such as Kriging, Cokriging, Splines [119], and artificial neural networks (ANN) [120]. Unfortunately, there is no criterion to predict the best one among interpolation techniques for a region, and we must evaluate the different interpolation techniques and then select the best one [120].

Many studies have employed interpolation techniques for the spatial estimation of climate parameters (*e. g.*, [121-123]) and air temperature (*e. g.*, [120, 124-128]). The studies have shown that spatial interpolation of temperature data can lead to considerable uncertainties and errors in the resulting temperature maps [129, 130]. Jarvis and Stuart [131] showed that the inclusion of some guiding variables within interpolation techniques using multi-variate linear regression technique could decrease the uncertainty and error of the interpolation techniques. They employed this technique for spatial distribution modelling of maximum and minimum daily air temperature in Wales and England. This approach is also a promising approach for development of air temperature maps in urban areas with fewer uncertainty and error.

The accuracy of the interpolation techniques is highly dependent on the number and the geographical distribution of the stations [132]. A small number of stations with irregular distribution lead to high estimation error. However, the density of air temperature measurements required to observe the spatial distribution of elevated air temperature in urban areas is not a constant, but takes on a different value in different cities [133]. In the planning stage of designing an air temperature network, choosing the optimal number of monitoring stations and their distribution is very important [134]. Bilonick [135, 136] pointed out that at least 50 stations are necessary for the stable estimation of monthly semi-variogram in State of New York. A small number of stations are insufficient for a reliable estimation of spatial heterogeneity. Although the meteorological parameters in urban scale have higher level of spatial heterogeneity than the regional scale, often in the cities, there are an insufficient number of meteorological stations providing climatic data, and they have an irregular geographical distribution [137]. Hence, it seems that interpolation methods are not so useful for the estimation of air temperature with high accuracy and resolution, especially in urban areas with miscellaneous surface materials, roughness height, vegetation and water fraction as well as low station density and irregular distribution.

We developed an air temperature map for Berlin by using the interpolation techniques. Figure 1 shows one sample of an air temperature map in Berlin, generated by optimized inverse-distance weighting technique.

The interpolation result was compared with the land use map of Berlin, fig. 2. During the daytime in May, the air temperature of water bodies, forests, and green urban areas in Berlin is lower than that of residential, commercial and industrial areas. It is clear that the interpolation results have no compatibility with the urban features because the interpolation techniques often only consider the position of stations as the input variables for the estimation and these techniques do not consider the major factors on air temperature. Although, interpolation techniques present high-resolution spatio-temporal air temperature mapping, they have no acceptable accuracy level.

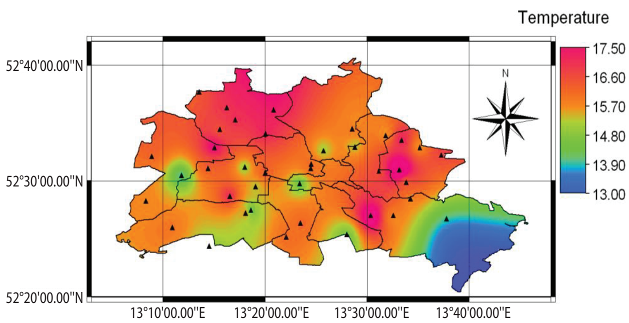


Figure 1. The location of air temperature monitoring stations (triangles) with the results of interpolation of hourly air temperature data [°C] (10:00, May 6, 2012) using inverse-distance weighting technique
(*for color image see journal web site*)

To improve the spatial modelling of air temperature in urban areas using interpolation techniques, it is useful to increase the amount of air temperature data and/or utilize the site selection technique to cover inner-city air temperature variations appropriately.

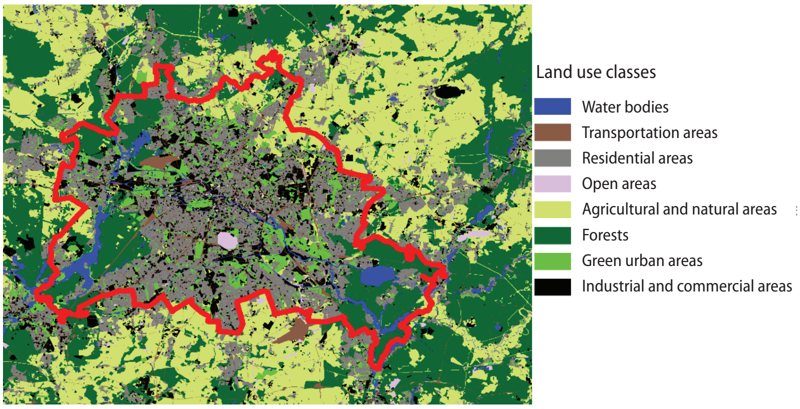


Figure 2. The land use map of Berlin and its surrounding areas (the red line shows the boundary of Berlin in metric co-ordinate system)
(*for color image see journal web site*)

A dense monitoring network is very advantageous in retrieving the spatial pattern of air temperature in urban areas using interpolation technique, and a dense monitoring network provides valuable information for the monitoring of elevated air temperature in urban areas [138]. Hence, Smoliak *et al.* [138] used a dense monitoring network to reveal the spatio-temporal pattern of air temperature in Minneapolis–St. Paul Minnesota, Minn., USA. They used two interpolation techniques (kriging and cokriging). Honjo *et al.* [134] studied air temperature in the Tokyo metropolitan area using a dense air temperature monitoring network. They found that it is possible to achieve a 30% reduction in the number of stations required if (in place of random sampling) a suitable clustering technique is employed to select the stations. They used inverse distance weighted (IDW) technique for interpolation. Site selection technique, as presented by Honjo *et al.* [134], leads not only to better performance with the same number of stations, but also sustains the same level of performance with fewer monitoring stations. The findings of Honjo *et al.* [134] are valuable for the optimization of air temperature monitoring networks in urban areas. Future studies should pay specific attention to the importance of optimizing monitoring networks and site selection techniques. Although a dense monitoring network is beneficial, it is expensive [68]. Hence, the idea of applying low cost air temperature sensors has been introduced and employed to provide near realtime air temperature data (*e. g.*, [68, 139, 140]). The field investigation showed that these low cost sensors have excellent performance root mean square error (RMSE) is 0.13 °C [68]. This approach is very useful for developing spatio-temporal air temperature maps in urban areas.

In addition, crowdsourcing has proved to be a valuable tool in the preparation of a large amount of air temperature data, and many different crowdsourcing projects for temperature data collection have been implemented [141]. Drobot *et al.* [142, 143] and Anderson *et al.* [144] used vehicles sensors for air temperature measurements. Mobile phone application is also utilized for the measurement of weather data using mobile phone sensors (wathersignal.com). Cassano [145] used low cost sensors installed on bicycles for temperature measurements. Overeem *et al.* [69] used a simple heat transfer model to convert battery temperature, measured by smart phones, to daily air temperature in eight urban areas. The mean absolute error (MAE) and coefficient of determination, R^2, of estimation of air temperature during summer and winter were 1.52 °C and 0.81, respectively. The MAE and R^2 for autumn and spring were 1.75 °C and 0.84, respectively. Although it is difficult to obtain accurate data from built-in smart phone sensors, calibration techniques can be employed to improve the accuracy of smart phone measurements [146]. In conclusion, crowd sourcing is a suitable and cost-effective tool for generating a large database of air temperature observations in urban areas, and it can be employed not only in air temperature retrieval algorithms (*e. g.*, interpolation and regression techniques), but also for data assimilation in simulation models [69, 141]. Although appropriate calibration, validation and quality control techniques must be adopted to increase the potential of crowdsourcing to provide a valuable source of high spatio-temporal resolution and real-time data, only a few studies have been performed [141]. Therefore, specific guidelines, standards and protocols are necessary to quantify the reliability of crowdsourcing data [141].

Regression techniques

In some studies, researchers tried to find the statistical relationships between air temperature and some of the climatological, geographical, and landscape variables using multi-variate linear and non-linear regression techniques, (*e. g.*, [147-154]):

$$T_a = g\left(x_1,\cdots,x_m\right) \tag{2}$$

where $x_1,\cdots,x_m$ are the m input variables which are the effective factors on the air temperature and g is a linear or non-linear function that relates the input variables to the air temperature, T_a.

Rigol *et al.* [120] employed ANN as a non-linear multi-variate regression technique for daily minimum air temperature estimation in UK. They showed that the employment of air temperature observations as input variables with the other effective factors on the air temperature has significant effects on the improvement of the results of multi-variate regression technique. The RMSE decreased from 3.15 °C to 1.15 °C and R^2 increased from 0.62 to 0.95.

Basically, multi-variate regression techniques can be used to simplify complex climatological relationships (model reduction) [154]. However, the statistical methods have a problem in that they may require many observations to reveal the pattern between the studied phenomenon and explanatory variables, especially when the modelling phenomenon has high spatial variation such as air temperature in the urban areas [155, 156]. This is one of the major limitations of the multi-variate regression techniques.

Although the preparation of required observations is time and cost consuming, employing a suitable experimental design technique [157] can lead to an optimum database of air temperature and explanatory variables which consider the effects of static and dynamic (spatial and temporal) parameters on air temperature. In addition, a well-designed measuring campaign, which suitably covers the domain of representative spatial variables, will avoid incidental collinearity [158]. Furthermore, as it was explained in previous section, data collection by crowdsourcing or utilization of low cost sensors is promising techniques for preparing the required data for regression techniques.

In some studies, researchers have tried to derive air temperature maps by linear correlation between air temperature and remotely sensed LST map [14, 70, 159-167]. We found that the typical range of errors in the studies on the linear correlation between LST and air temperature is about 2-3 K.

Although global spatio-temporal variability of LST and air temperature is similar, local LST and air temperature are significantly different [1]. They showed that the air temperature is higher than LST during the night-time, but it is lower than LST during the daytime. It means that there is no linear correlation between LST and air temperature under high spatial and temporal resolutions. Other studies showed that the correlation between air temperature and LST depends on land cover and sky conditions [168, 169] and sometimes the linear relation between air temperature and LST data shows high level of error [170]. Therefore, linear correlation between LST and air temperature can not be a reliable method for direct estimation of air temperature in high spatial and temporal resolutions.

Hence, employment of advanced non-linear regression approaches such as modified active learning method (ALM) [171], support vector regression [172, 173], adaptive network-based fuzzy inference system [174, 175], and multi-variate adaptive regression splines [176, 177] are proposed for further studies on the modelling of high-resolution air temperature in the urban areas using multi-variate regression techniques. In the previous studies, the combination of collinearity reduction and feature selection/reduction techniques has not often utilized for the elimination of the disadvantages of collinear, redundant, and irrelevant input variables in the modelling of air temperature in the urban areas.

In addition, utilization of two major pre-processing on data (collinearity reduction and feature selection/reduction) before the implementation of non-linear regression approaches is also suggested for improvement of the results.

Severe non-orthogonality in the input variables or high linear correlation among the input variables is named *Collinearity* [158, 178]. The results of regression analysis using collinear variables are ambiguous, sensitivity analysis and determination of the effects of individual variables is impossible, and the developed regression model is not robust and it is sensitive to small changes in the data [158, 178]. Before any feature selection technique, the collinearity must be reduced, because application of feature selection procedure on the collinear input variables can lead to inappropriate feature selection and model development [179, 180]. For more details about collinearity diagnostic and reduction techniques, refer to Dormann *et al.* [158] and Chatterjee and Hadi [178].

When there are many irrelevant and redundant input variables in the multi-variate modelling, the knowledge extraction is very hard for the modelling technique. There are two approaches to deal with the mentioned problems in the modelling using the high dimensional input variables: feature reduction [181-183] and feature selection [184-186].

In the previous studies, the combination of collinearity reduction and feature selection/reduction techniques has not often utilized for the elimination of the disadvantages of collinear, redundant, and irrelevant input variables in the modelling of air temperature in the urban areas. In addition, the combination of collinearity reduction and feature selection/reduction techniques has not often utilized for the elimination of the disadvantages of collinear, redundant, and irrelevant input variables in the modelling of air temperature in urban areas.

Some studies tried to retrieve air temperature from the combination of LST and vegetation maps, derived from satellite images (*e. g.*, the temperature/vegetation index – TVX) [4, 71-74, 187-189]. The studies showed that the TVX method is a suitable technique for the estimation of air temperature for large regions with gradual temperature changes (*e. g.*, [160, 165, 190, 191]) but not suitable for urban areas [77]. Furthermore, this technique show typically a RMSE about 3-4 °C for air temperature estimation [192].

Multi-variate linear and non-linear regression using the satellite derived LST and other effective factors on air temperature are other techniques for the estimation of air temperature (*e. g.*, [77, 193-197]). We extracted air temperature from MODIS products using a multi-variate non-linear regression technique, entitled ALM [172, 198]. The results of hourly air temperature estimation have been presented in fig. 3. The input variables were the satellite-derived data (LST, emissivity, radiance, view angle, water vapour). The comparison between figs. 3 and 1 implies that the fig. 3 has better compatibility with land use (fig. 2) than interpolation techniques and multi-variate regression technique seems better than interpolation technique. However it is resolution (1 km) is not so high.

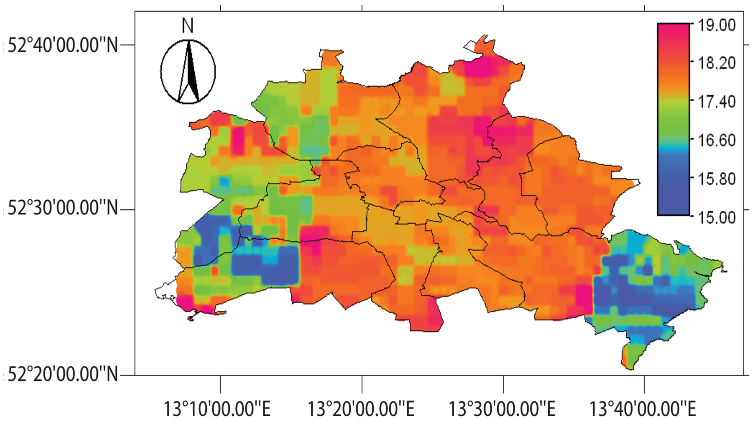


Figure 3. Hourly air temperature map of Berlin [°C] (10:00, May 6, 2012), derived from MODIS image using a non-linear multivariate regression technique (*for color image see journal web site*)

One of the major sources of error in the thermal remote sensing techniques is related to the uncertainties of LST estimation. Cloud contamination, due to a failure of the cloud detection algorithm, surface emissivity, view angle, CO_2, water vapour, relative humidity, wind speed, and soil moisture are known as the major sources of uncertainties of LST (*e. g.*, [1, 199, 200]). In addition, satellite images make a trade-off between the temporal and the spatial resolution. For example, the images of thermal band of MODIS have daily temporal resolution and 1 km spatial resolution, but thermal images of LANDSAT-TM/ETM+ have 16-day temporal resolution and 60 m spatial resolution. The higher temporal resolution leads to low spatial resolution and vice versa [36]. However, several studies have been performed for the downscaling of LST, derived of geostationary satellites (*e. g.*, [201, 202]), the results typically show more than 2 K error.

In addition, the thermal remote sensing approach is not applicable under cloudy conditions and development of continuous air temperature with high temporal resolution in the mostly cloudy urban areas (*e. g.*, Berlin, median cloud cover: 85%) is difficult. This is the major limitation of the thermal remote sensing approach for the development of continuous air temperature maps with high accuracy and resolution.

Simulation techniques

Another approach for air temperature estimation is the simulation using mathematical simulation models, which attempt to consider the processes involved in air temperature. Generally, four groups of simulation techniques have been developed for air temperature estimation, which are energy balance models, micro scale CFD models, mesoscale numerical weather prediction (NWP) models and coupled models.

The energy balance budget for a building canyon was first suggested by Oke [203]. The energy balance modelling approach considers air temperature to be controlled by the radiation balance, and this approach uses the energy conservation equation for a given control volume. The effects of atmospheric phenomena, turbulence fluctuations, and velocity field are presented as the heat fluxes in the energy conservation equation and these fluxes are generally defined by analytical or empirical equations and in the other words, the temperature and velocity fields are separated in energy balance models [6, 78, 204, 205]. The urban canopy models (UCM) are derived from the energy balance equation. Grimmond *et al.* [35] have presented a review of 33 urban energy balance models and their performances in urban cases. In addition, Best and Grimmond [206] compared 16 energy balance models and attempted to determine the dominant physical processes. A coupled model of single layer UCM and single column model (SCM) was employed to predict urban surface energy and water budget with improved accuracy in Phoenix, Ariz., USA, [207]. The SCM [208, 209] is able to predict the spatio-temporal variations of temperature in the atmospheric boundary layer [207]. The utilized UCM includes an urban hydrological model to improve latent heat prediction, developed by Wang *et al.* [210]. This coupled model showed robust results and the studied scenarios using the coupled model demonstrated that cool and green roofs have a significant impact on the mitigation of elevated temperature in urban areas [207]. Although the heat exchange among urban elements is often considered in the UCM, vegetation and its interaction with urban elements has only been considered in a few models (*e. g.*, [211, 212]).

Energy balance models generally have high spatial and temporal resolutions [35]. These models need three groups of input variables: urban parameters to describe the details of urban area, such as surface morphology and albedo, time series of boundary conditions, and initial conditions. About 150 different parameters and state variables are needed in the energy balance models [35].

Although some methods have been presented to reduce to computational cost of parametrizations ([*e. g.*, [213], appropriate parameterization of building canopies and urban structures and increase of resolution in a city is very expensive in terms of computational time and cost [214], and comprehensive spatially-distributed parameters are rarely available at the high-resolution [192]. Hence, the city has been replaced with homogeneous columns of similar buildings in some studies [215], but it decreases the spatial resolution of the model and the model can not be applicable for study of the thermal comfort at pedestrian level [35].

Future studies on simulation using UCM must focus on quantifying the model uncertainties and developing suitable parametrization techniques and efficient numerical procedures [207]. However, the precision of UCM is highly related to the urban database [216]. Combining the coupled model with NWP models will be useful when running the model for prediction, and will be particularly applicable to the future development of sustainable cities [207]. These activities will improve the performance and accuracy of UCM for spatio-temporal modelling and prediction of air temperature in urban areas.

In addition, absence of high air velocity fields in energy balance models is their major weakness. The latter are necessary to consider the effects of flow patterns (*e. g.*, eddy circulation, wake region, and turbulence), to study the formation of the atmospheric phenomena (*e. g.*, precipitation and stratification), and to determine the sensible and latent heat fluxes [66]. Also, the assumption of these fluxes with empirical correlations does not appropriately represent the interaction between velocity and temperature fields [66].

Integrated urban land models (IUM) have recently been developed, which integrate the energy balance model with water balance model, (*e. g.*, [217]). Further studies are necessary to develop more sophisticated models, which can appropriately incorporate land-atmosphere interactions. The IUM will also be coupled with weather prediction models in the near future, making a promising prediction model for urban areas [217].

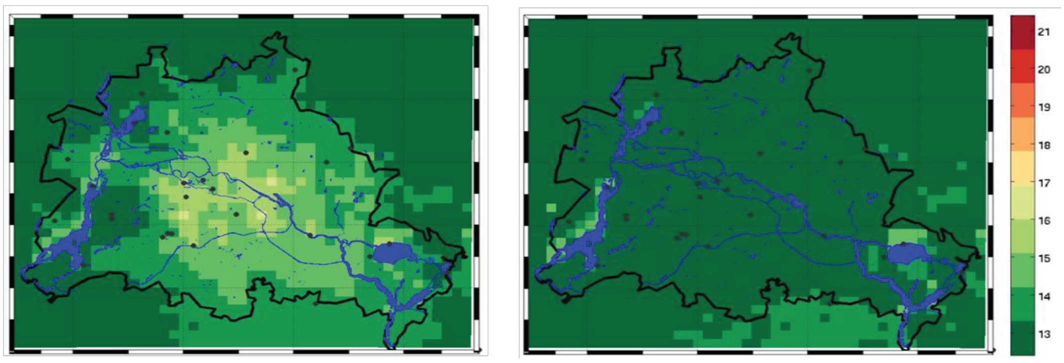
Micro scale CFD models simultaneously solve the conservation of mass, potential temperature, momentum, and species (water vapour and chemical reaction). These micro scale models are not applicable for an entire city, with all of its detail, because of the high computational cost. Therefore, the simulation in micro scale is limited to a small domain of some blocks of buildings (a few hundred meters, *e. g.* ENVI-met [218]).

The mesoscale NWP models such as MM5 [219], RAMS [220], ARPS [221, 222], and COSMO-CLM [223] have smaller domain than synoptic-scale and larger domain than micro scale models. The horizontal resolution of these models is approximately ranged from one to several-hundred kilometres. Figure 4(a) presents the spatial distribution of air temperature in Berlin, estimated by COSMO-CLM. Figure 4(b) not only has low resolution (1 km) but also its pattern is not compatible with urban land use (fig. 2) and it has presented almost the same air temperature values for all of the land uses inside and outside of Berlin. Hence, these models are not suitable for the development of high spatial resolution maps in urban areas.

The coupled models (often coupled a mesoscale model with energy balance model) is the fourth approach toward air temperature calculation. The coupled model have been applied to major metropolitan regions around the world (*e. g.*, Nanjing, Houston, Beijing, Guangzhou/Hong Kong, Athens, Tokyo, and Berlin) to better understand the contribution of urbanization in air temperature, urban heat island, boundary layer structure and heat wave events (*e. g.*, [98, 225-231]). A common concern with the use of these complex models is the high level of uncertainty in the specification of surface cover and geometric parameters [232]. The spatial resolution of coupled models is often 1 km and more than 1 km. Figure 4(a) shows the results of air temperature simulation using the coupled COSMO-CLM model with an urban canopy model double canyon effect parametrization – (DCEP) [98]. Although the coupled model, fig. 4(a) has exhibited more compatibility with land use map (fig. 2) than the mesoscale model, fig. 4(b), but it has no high-resolution. It has been pointed out that the increase in the spatial resolution of the models increases the complexity of the model and CPU time because of need to the detailed parametrization of urban land use for determination of morphological and thermal characteristics of the urban area [230]. In total, a huge amount of urban details is required in order to achieve a suitable high-resolution urban model, and the increased cost and computational time of the simulation approaches has led to the exploration of new methods [233].

Summary and conclusions

This study presented the importance of the air temperature and its different effects. Then, the methods that have been widely used to estimate air temperature, especially in the urban areas (interpolation techniques, regression, and simulation techniques) were introduced and



(a) (b)

Figure 4. The spatial distribution of night-time air temperature in Berlin with one km resolution (2012/09/01, 22:00 UTC), developed by; (a) coupled COSMO-CLM with DCEP, (b) COSMO-CLM without DCEP [224] (*for color image see journal web site*)

the application of these approaches for high-resolution air temperature mapping with emphasis on the urban areas was reviewed and the advantages and limitations of the current approaches were presented. In addition, different air temperature modelling approaches were applied to Berlin, and the results of different techniques were evaluated.

Utilizing interpolation techniques is very easy and straightforward, and interpolation techniques can produce high-resolution spatio-temporal maps of air temperature. There are no criteria, however, to predict the best among different interpolation techniques for a region. Different interpolation techniques must be evaluated, and the best one selected. Although spatial interpolation of temperature data may lead to considerable uncertainties and errors, the inclusion of some guiding variables within interpolation techniques using multi-variate linear regression technique can decrease the uncertainty and error of the interpolation techniques. In addition, the utilization of a small number of stations with irregular distribution in interpolations may lead to high estimation error. A number of solutions have been developed to combat this problem. Some studies have attempted to employ dense observation networks, but this is not cost effective, so site selection techniques have been introduced to minimize the required number of observations. Low cost air temperature sensors have been suggested to decrease the observation cost. Furthermore, crowdsourcing has been used as a suitable and cost effective tool to generate a big database of air temperature observations in urban areas. Crowdsourcing can be employed not only in air temperature retrieval algorithms (*e. g.*, interpolation and regression techniques), but also for data assimilation in simulation models. Although appropriate calibration, validation and quality control techniques must be adopted to increase the potential of crowdsourcing data to provide a valuable source of high spatio-temporal resolution and real-time data, only a few studies have been performed. Therefore, further studies into the calibration and validation of crowdsourcing data, as well as the preparation of specific guidelines, standards, and protocols, are necessary to improve accuracy and quantify the reliability of crowdsourcing data. Utilization of the previous techniques is a promising approach to achieving a suitably high-resolution spatio-temporal mapping of air temperature.

Regression using linear techniques is very easy and it produces high-resolution spatio-temporal maps, but these techniques are problematic in that they may require many observations to reveal the pattern between the air temperature and explanatory variables. A well-designed measuring campaign can decrease the amount of required data. Crowdsourcing data collection techniques can also be beneficial. Furthermore, utilizing air temperature data in a representative station as an input variable, and employing non-linear techniques with pre-processing on input variables (*e. g.*, feature selection/reduction and collinearity reduction techniques), can increase the accuracy and performance of regression technique. In some studies, the remotely sensed LST data, retrieved from thermal images, have been used in the regression techniques. The major limitations in the regression techniques using remotely sensed LST are the uncertainties of LST estimation, non-linear relationship between LST and air temperature, trade-off between the temporal and the spatial resolution. In addition, the thermal remote sensing approach is not applicable under cloudy conditions. Accordingly, the regression techniques using remotely sensed LST is not suitable for continuous high-resolution mapping of air temperature in the urban areas. Several studies have recently been performed into the downscaling of LST, and the generation of high-resolution spatio-temporal maps of LST, but the results typically show more than 2 K error. Hence, further studies are necessary into the extraction of accurate high-resolution spatio-temporal maps of LST from remotely sensed data. Future studies on non-linear regression techniques using accurate and high-resolution LST data will then be promising approaches to developing suitable high-resolution air temperature maps in urban areas.

Four groups of simulation techniques have been developed for air temperature and urban heat island (UHI) estimation: micro-scale CFD models, mesoscale NWP models, energy balance models, and coupled models. The micro-scale CFD models have high spatio-temporal resolution but they are limited to a small domain of some blocks of buildings and they are not applicable for an entire city. Although the mesoscale models have high temporal resolution, they have no high spatial resolution. These models do not consider the urban structures, so these models present non-suitable air temperature patterns in urban areas. Energy balance models have high spatio-temporal resolution. These models are complicated and they need too many parameters and variables. In addition, there is a high level of uncertainties in the parametrizations. Appropriate parameterization of building canopies and urban structures in a city is very expensive in terms of time and computer load. Therefore, future studies into simulations using energy balance models must focus on quantifying the model uncertainties and developing suitable parameterization techniques and efficient numerical procedures. In addition, a model integrating the energy balance model and water balance model IUM, has recently been presented, and is a promising new approach to suitable air temperature modeling in urban areas. However, further studies are necessary to develop more sophisticated models to appropriately incorporate land-atmosphere interactions in IUM. Coupled models (often a mesoscale model coupled with an energy balance model) can present suitable spatial air temperature patterns in urban areas, and have high temporal resolution. However, increasing the spatial resolution of a coupled model requires a huge amount of urban data and computational cost. The IUM will be coupled with weather prediction models in the near future, and will be a promising new approach to air temperature prediction in urban areas.

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