Assessment of thermal anisotropy on remote estimation of urban thermal inertia

Wenfeng Zhan, Yunhao Chen, James A. Voogt, Ji Zhou, Jinfei Wang, Wei Ma, Wenyu Liu

ABSTRACT

Thermal inertia over vast earth surfaces is a crucial parameter in many related disciplines. However, remote estimates of urban thermal inertia show anisotropy effects due to thermal anisotropy. This study investigates the impacts of thermal anisotropy on the estimation of urban thermal inertia. We present the concepts of DTI (directional thermal inertia) and DATI (directional apparent thermal inertia) to describe this anisotropic effect. A combined approach to estimating thermal inertia named NLS (nonlinear least square) is proposed as a compromise solution using temporal temperature measurements. Intercomparisons between methods are indirectly conducted by predicting surface temperatures, and the results indicate the NLS has higher accuracy of 1 to 2 K. The DTI estimation over an urban scale model, together with flat concrete and grass surfaces, reveals that the DTI intensity is significant when DRTs (directional radiometric temperatures) are used as inputs. Over the scale model, the DTI and DATI values range from 0.028 to 0.038 K and from 1530 to 2970 W m$^{-2}$, respectively. Further discussions demonstrate that DTI intensity has an approximate linear relationship with DTI intensity and that it thus could be used as a predictor of DTI intensity. We finally propose that using complete urban surface temperatures instead of the DRT would be better to estimate urban thermal inertia from the perspective of surface energy balance.

1. Introduction

In the remote sensing of land surfaces, thermal inertia is usually defined as a measure that quantifies the variation amplitude of land surface temperatures (LSTs). This parameter describes the degree an object impedes the temperature fluctuation. As a significant indicator, thermal inertia is not just a shallow surface property but a volumetric identity. In the past few decades, thermal inertia has provided attractive ways to estimate regional evapotranspiration (Moran et al., 2009; Stisen et al., 2008), deduce soil heat flux (Murray & Verhoef, 2007a, 2007b), monitor soil moisture (Verstraeten et al., 2006; Yu & Tian, 1997), analyze UHIs (urban heat islands) (Hafner & Kidder, 1999; Wang et al., 2007), determine lithology and produce geological maps (Mitra & Majumdar, 2004; Nasipuri et al., 2006, 2005). Thermal inertia also plays an important role as one of the key factors in predicting diurnal LSTs (Price, 1977) and in exploring the thermal properties of other planets, such as Mars (Mellon et al., 2000; Putzig et al., 2005). Over urban areas particularly, thermal inertia affects the azimuth gap between the sun and the hotspot, which was termed as the thermal inertia effect by Lagouarde et al. (2010).

In the remote sensing community, approaches that invert thermal inertia from satellite data have become possible as a result of thermal sensors. When the thermal conductivity ($\lambda$) and heat capacity ($C$) are available, thermal inertia can be directly determined by these provided parameters. However, because of the high heterogeneity of land surfaces, these three parameters are as difficult to obtain as thermal inertia itself; therefore, indirect methods of estimating thermal inertia have been developed. Theoretically, most methods for estimating thermal inertia by remote sensing are derived from the heat conduction equation (HCE), which is associated with certain boundary conditions typically constrained by the surface energy balance (SEB) equation. The difference among these methods is from the specific strategy in parameterizing the boundary condition.

We divide these classical techniques into five categories: the Laplace Transform (LT) (Watson, 1973), the Discretization Method (DM) (Carlson et al., 1981; Ho, 1987; Kahle, 1977), the Fourier Transform (FT) (Abdellaoui et al., 1986; Price, 1977), the Iterative Method (IM) (Rafly & Becker, 1986), and the Physical Method (PM) (Verhoef, 2004). However, in the past two decades, the majority of studies have tended to use FT to derive a relationship expressed by sinusoidal functions between thermal inertia and LST at a certain depth or to...
use PM to directly estimate thermal inertia by night cooling or soil properties. (1) Examples of FT include Xue and Cracknell (1995), Yu and Tian (1997), Sobrino and El Kharrarz (1999a, 1999b), Liu and Zhao (2006), and Cai et al. (2007). Compared with Price (1977), the method by Xue and Cracknell (1995) utilizes much less meteorological data from field experiments, and it shows advantages for thermal data from polar-orbit satellites. Sobrino and El Kharrarz (1999a, 1999b) improved this method by proposing the FTA (Four Temperature Algorithm) without using any field measurements except satellite data. In Liu and Zhao (2006), the model accuracy was modified by measured sensible and latent heat fluxes. (2) Examples of PM include Verhoef (2004), Murray and Verhoef (2007a, 2007b), and several others. Verhoef (2004) utilized the LST differences between sunset and sunrise during the nighttime. This study was followed by Murray and Verhoef (2007a, 2007b), which addressed the importance of physical properties such as soil porosity and moisture content, rather than environmental forcing, to estimate thermal inertia.

2. Problems and definitions

2.1. Problems

Although the estimation of thermal inertia using remote sensing has advanced in the last several decades, problems remain.

The earliest concept of thermal inertia, written as $\sqrt{AD}$ (Price, 1977) or written as $C/\sqrt{D}$ $(D$ is thermal diffusivity) (Verhoef, 2004), only depends on the physical property of objects and is thus unrelated to observers (remote sensing) and shows no directionality (i.e., isotropy). The estimation of thermal inertia over extensive and heterogeneous land surfaces would be almost impossible if LSTs from remote sensing are unavailable. However, one large concern that has been raised in many studies is that most earth surfaces, including vegetation (Paw, 1992), snow (Dozier & Warren, 1982), urban (Voogt & Oke, 1998a, 1998b; Zhan et al., 2010b), which has urged the assessment of the thermal inertia estimated from directional temperatures. The intensity of DATI and DTI is thus defined as:

$$ l_{DATI} = \max \{DATI(\varphi_0) - DATI(\varphi_\phi)\}, R_{DATI} = \max \{DATI(\varphi_0)/DATI(\varphi_\phi)\} $$

$$ l_{DTI} = \max \{DTI(\varphi_0) - DTI(\varphi_\phi)\}, R_{DTI} = \max \{DTI(\varphi_0)/DTI(\varphi_\phi)\} $$

where $\varphi_0$ and $\varphi_\phi$ represent two observation angles; $l_{DATI}$ and $l_{DTI}$ are the differential intensity of DATI and DTI; and $R_{DATI}$ and $R_{DTI}$ convey the ratio intensity. The combined differential and ratio assessments describe the intensity of directional urban thermal inertia caused by thermal anisotropy.

In this study, the remote estimation of thermal inertia is improved by the appearance of temporal observations of LST. The DTI intensity in typical urban areas is assessed using theoretical deductions, computational simulations, and field measurements. The intent is to provide new methods for estimating the impacts of DTI due to directional observation and to offer a micro-scale perspective to study this issue. We also illustrate how, as a volumetric quantity without directionality, the estimation of thermal inertia produces anisotropy as a result of temporal and directional LST observations.

3. Methodology

3.1. Field measurements and data preparation

A brief overview of the field experiments and data processing techniques is presented here. Building blocks are one of the most commonly distributed urban targets. Other typical land covers included are trees, and flat surfaces of concrete and grasses. A field investigation was held at the Fangshan Experimental Research Base of Beijing Normal University in August 2008. Several thermal detectors were used, including thermal imager equipment (Fluke IR-FlexCam8800, band range: 8–14 μm,IFOV: 17°×14°, accuracy: ±2%), two handheld infrared radiation thermometers (Testo-845, accuracy: ±0.75 K) and several fixed infrared thermometers (RayTeK, IFOV: 2.86° and 53.13°, accuracy: ±1%).

3.1.1. Scale model and flat surfaces

It is a difficult task to measure the surface temperature distribution of real urban buildings because of the highly heterogeneous materials and structures. For simplicity, we construct a scale model that is composed of hollow concrete blocks that is downsized from real urban targets (see Fig. 1a). This downsizing technique was once widely employed to study urban thermal anisotropy and micro-meteorology (Kanda et al., 2005a, 2005b; Soux et al., 2004). The backgrounds of the scale model are impervious concrete. To confine a fixed FOV and to avoid strong FOV effects (Zhan et al., 2010b), we laid a circular aluminum frame on the top of the model. The aluminum was chosen for its low emissivity. The downward pointing sensor aims at the center of one block (i.e., building). The geometry of scale model is presented in Table 1.

Urban blocks are not the only urban land cover types; there are also vast flat concrete and grass surfaces distributed throughout metropolitan areas (see Fig. 1b). Real concrete and grasses were observed, and their thermal anisotropies were measured. Note that
the concrete surface is not pure in the vertical profile but is composed of several layers, including a thin layer of concrete on the surface, a thin layer of subsurface pebbles and stones, and a thick layer of compacted soil (Huang, 2009).

3.1.2. Directional temperature measurements

We designed two types of Movable Devices for Directional Temperature Observation (MDDTO1 and MDDTO2) (see Fig. 1a) to measure the directional temperatures. MDDTO1 is characterized by its weightiness and is designed for urban scale models, and its onboard sensors can be raised as high as approximately 6 m. Thermal images by IR-FlexCam8800, together with photos by SonyH-50, can be obtained at any zenith and azimuth. Another type of MDDTO (type 2, see Fig. 1b) was invented as a simpler type of equipment to acquire directional temperatures. MDDTO2 has a fine performance and takes only 10–20 s to carry out a measurement in a single direction. One usage of MDDTO2 is to measure the directional temperatures of flat concrete and grasses quickly.

3.1.3. Component temperature measurements

The urban scale model is divided into 11 components including the grounds, walls and roofs in both sunlit and shaded status (see Table 2). The component temperatures were once acquired through measurements (Voogt, 2008) or simulations (Lagouarde et al., 2010). In this study, these temperatures were obtained through thermal imager and thermometers, which were calibrated by a blackbody. The results are averages of the values from the different instruments used (Fig. 2).

The component temperatures displayed in Fig. 2 indicate that different components behave quite differently: (1) The temperatures of the sunlit components are much higher than the shaded components. (2) The temperature differences among components have the lowest values just prior to sunrise or just after sunset. (3) The roof component has the largest diurnal variation while the shaded ground has the lowest. The roofs receive large amounts of solar radiation during
the daytime, but at night, their cooling rates are large because the sky view factor is essentially 1.0, and there is no influence of multiple reflections of long-wave radiation between vertical walls and the ground. Moreover, the exposure of roofs to higher wind speeds likely enhances the convection heat loss. (4) The temperatures of walls and roofs achieve their peak values earlier (see $\Delta T$ in Fig. 2) than the ground because the ground has a larger potential store of energy and may thus have surface temperatures that vary more slowly in time than that of the buildings.

### 3.2. Simulation of DRT

For the scale model, we design a Computer Model to Simulate the Thermal Infrared Radiation of 3-D urban targets (CoMSTIR) (Ma, 2009). CoMSTIR models the transfer of thermal radiation from urban surfaces to remote sensors and it provides the directional temperature of urban surfaces received by a thermal sensor. The scale model is virtualized in the computer using OpenGL (Open Graphics Library), which is a cross-platform API (application programming interface) that produces 3-D computer graphics. The computed model scale utilizes the same geometrical attributes of the real scale model (see Table 1). CoMSTIR requires three categories of parameters as inputs including the solar and sensor positions and measured component temperatures (see Fig. 2). The directional temperatures can be modeled using CoMSTIR if these inputs are available. Different radiation regimes are utilized as calculators to estimate the component fractions. Among these regimes, the radiosity is the best (Zhan et al., 2010a). Intercomparisons with field measurements indicate that CoMSTIR achieves convincing accuracy (Ma, 2009).

For concrete and grasses, many approaches that are intended to model the directional thermal emission, including CoMSTIR, are incapable of demonstrating the thermal directionality of relatively flat surfaces provoked by micro-structures. Micro-structure geometry is difficult to represent, but all these approaches have been planned on the premise of the component concept, which is based on the material and 3-D structure and is then strengthened by solar radiation. Fortunately, MDDTO2, characterized by its high mobility and convenience in measurements, is able to obtain the directional temperatures at all 13 of the planned observation angles (zenith = $-60^\circ$, $-50^\circ$, ... $0^\circ$, ..., $60^\circ$) in less than 2 min. The error induced by the temporal change of LST is minor in such a short period. We thus use the directional observations from MDDTO2 to substitute computational simulation.

### 3.3. Remote estimation of thermal inertia

In remote sensing, ATI is quite direct and is usually written as $\text{ATI} = (1 - \alpha)/\Delta T$, where $\alpha$ and $\Delta T$ are the albedo and the amplitude of diurnal LST (Price, 1985). For thermal inertia itself, the process is more difficult. As indicated above, it would be better to assess the impact of thermal anisotropy if less meteorological data were used for the remote estimation of urban thermal inertia because too many factors as inputs would complicate the assessments. We propose a derivative method to estimate thermal inertia only by temporal surface temperatures. The model is derived from Price (1977), Xue and Cracknell (1995), and Sobrino and El Kharraz (1999a) but has less meteorological data inputs than these models except the one by Sobrino and El Kharraz (1999a). All LST observations are combined to solve heat conduction equation (HCE) to acquire the undetermined thermal inertia, forming a nonlinear least square (NLS) technique.

We begin from the HCE on semi-infinite and homogeneous solid media under periodic heating (Price, 1977):

$$D \frac{\partial^2 T(x, t)}{\partial x^2} = \frac{\partial T(x, t)}{\partial t}$$

(2)

where $D$ is the thermal diffusivity (in m$^2$s$^{-1}$), and $T(x, t)$ is the temperature (in K) at the depth of $x$ (in m) and the time of $t$ (in second). The HCE given by Eq. (2) is constrained by a boundary condition given by (Yu & Tian, 1997):

$$-\lambda \frac{\partial T(x, t)}{\partial x} \bigg|_{x=0} = G = R_s + (R_l - R_e - H - LE) = R_s + [h_0 + h_1 T(0, t)]$$

$$R_s = (1 - \alpha) S_0 \tau \cos Z$$

(3)

where $\lambda$ is the thermal conductivity (in Wm$^{-1}$K$^{-1}$); $G$ is the ground heat flux (in Wm$^{-2}$); $R_s$ is the solar shortwave radiation (in Wm$^{-2}$); $R_l$ is the downward atmospheric longwave radiation (in Wm$^{-2}$); $R_e$ is the emitted surface thermal radiation (in Wm$^{-2}$); $H$ and $LE$ are the sensible and latent heat fluxes, respectively (in Wm$^{-2}$); $h_0$ and $h_1$, which are used to simplify $(R_l - R_e - H - LE)$, are the constant and linear coefficients of surface temperature (Watson, 1973); $\alpha$ is the surface albedo; $S_0$ is the solar constant at the top of the atmosphere, usually designated as 1361 W m$^{-2}$; $\tau$ is the atmospheric transmittance; and $Z$ is the solar zenith angle. $Z$ satisfies the following:

$$\cos Z = \sin \gamma \sin \theta + \cos \gamma \cos \theta \cos (\alpha \omega)$$

(4)

where $\gamma$ and $\theta$ are the solar declination and local latitude respectively; and $\omega$ is the frequency of diurnal variation, given as $2\pi/(24 \times 3600)$.

The solution for the HCE of Eq. (2) under the boundary condition of Eq. (3) can be derived as (Xue & Cracknell, 1995):

$$T(0, t) = -\frac{h_0}{h_1} + (1 - \alpha) S_0 \tau \sum_{n=1}^{m} A_n \frac{\cos(n \omega t - \delta_n)}{\sqrt{n \omega t^2 + 2 \alpha h_1 P + h_1^2}}$$

(5)

where $P$ is the thermal inertia (in TIU, 1 TIU = 1 Ws$^{1/2}$/m$^{-2}$K$^{-1}$) (Sobrino & El Kharraz, 1999a); and $A_n$ and $\delta_n$ are the Fourier coefficient and phase bias at the $nth$ scale, written as:

$$\psi = \arccos(tan \gamma \tan \theta)$$

$$\delta_n = \arctan\left(\frac{P \sqrt{n \omega t}}{\sqrt{2} h_1 + P \sqrt{n \omega t}}\right)$$

$$A_1 = \frac{2}{\pi} \sin \gamma \sin \theta \sin \psi + \frac{1}{\pi} \cos \gamma \cos \theta |\sin(2\psi)| + 2\psi$$

$$A_n = \frac{2}{\pi n \omega t \sin(\psi)} \cos \sin(\psi) + \frac{1}{2} \cos \cos \theta |\sin(n \omega t - \psi)| \cos \psi$$

(6)

$$\cos \cos \theta |\sin(n \omega t - \psi)| \cos \psi$$

Eq. (5) provides the relationship between the unknowns ($h_0$, $h_1$, and $P$) and the diurnal surface LST, and it is further simplified as:

$$T(0, t) = g(h_0, h_1, P, t)$$

(7)

where $g(\cdot)$ represents the relationship. Theoretically, Eq. (7) is solvable if more than three LST records are available. In this study, temporal LST records are abundant. We determine the unknowns through designing a cost function ($J$) that minimizes the errors between the observed and predicted LSTs. The cost function is designed as:

$$\min J = \sum_{t=1}^{N} \left| T(0, t) - g(h_0, h_1, P, t) \right|^2$$

(8)

where $J$ is the cost function; and $N$ is the observation number. We utilize the Levenberg-Marquardt method to minimize $J$ due to the associated robustness (Marquardt, 1963). It is thus possible to obtain unbiased thermal inertia with more LSTs using NLS (nonlinear least square), which equalizes all LST records and minimizes the integrated errors (further validations are in Section 5).
4. Temporal thermal anisotropy

4.1. Scale model

With measured component temperatures as inputs, CoMSTIR is performed to produce diurnal polar-DRT (directional radiometric temperature) figures (see Fig. 3) over the scale model. Fig. 3 indicates that thermal anisotropy over the scale model between sunrise and sunset behaves rather differently than that at nighttime. The temporal results confirm that an intense hotspot effect occurs during the daytime, which has been observed in previous studies (Lagouarde et al., 2010; Soux et al., 2004; Voogt, 2008). The DRT of daytime reaches the highest point in the south semi-sphere of the polarization figures because sunlight always comes from the southern space in the mid or high latitudes of the north globe. This result implies that solar geometry combined with building spacing controls the appearance of the hotspots. Nighttime patterns are completely different because the pattern of long-wave radiation loss, rather than shortwave radiation gain, controls the pattern of the component temperatures and, hence, DRT.

The moments of extreme intensity of thermal anisotropy are closely related to the magnitude of differences among component temperatures. The minimum intensity of thermal anisotropy occurs at approximately 05:00 (Fig. 3c) and 19:00 (Fig. 3j), either just prior to sunrise or subsequent to sunset. The maximum appears close to solar noon (Fig. 3f–h). The thermal anisotropy reveals that the diurnal of the polarization figures because sunlight always comes from the southern space in the mid or high latitudes of the north globe. This result implies that solar geometry combined with building spacing controls the appearance of the hotspots. Nighttime patterns are completely different because the pattern of long-wave radiation loss, rather than shortwave radiation gain, controls the pattern of the component temperatures and, hence, DRT.

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Fig. 3. The polar-DRT over the scale model. The thermal anisotropy of the scale model is represented at every 2 h in a diurnal cycle.
LST cycles oscillate under varying zeniths and azimuths in directional measurements. Parts of the fluctuations are demonstrated in Fig. 4. Fig. 4 shows temporal variations of DRT at zeniths of 30° and 60°. These oscillations suggest again that the DRT variations are dependent on illumination status. For the scale model, the range of diurnal DRT reaches the highest when the observations are at an azimuth of approximately 225°, and it reaches the lowest when sensors are in the opposite direction (i.e., at an azimuth of approximately 45°), although this might change with different building geometries.

### 4.2. Flat surfaces

MDDTO2 was used to obtain directional temperatures, and the results relating to concrete are presented in Fig. 5a, with the DRT scattered by the zenith (°) and time of day (h). Further clarifications are highlighted by being projected onto two-dimensional planes (see Fig. 5b and c).

Fig. 5 shows the following: (1) Flat concrete shows an intensity of thermal anisotropy of approximately 2 K, and (2) this intensity remains almost unchanged during the daytime if the records influenced by clouds are discarded (see Fig. 5b). This invariability of intensity is an indicator that the illumination status, governed by solar and surface geometry, is the less important factor in determining the thermal anisotropy of flat concrete. The directionality is thus mainly caused by the material and micro-structure of the concrete itself and additionally is likely caused by the FOV effect (Zhan et al., 2010b). (3) There is no apparent hotspot effect observed because of the approximately symmetrical distribution of DRTs by zenith (the symmetric axis is at a zenith of 0°; see Fig. 5c).

For urban low grasses, the temporal DRTs shown in Fig. 6 indicate that the urban lawns show a lower intensity of thermal anisotropy than urban buildings related to the solar geometry, varying from approximately 1 to 4 K, which is similar to previous studies (Coret et al., 2004; Lagouarde et al., 2000; Liu et al., 2007). The intensity of thermal anisotropy on grasses fluctuates more than that of concrete ground perhaps because grasses, compared with flat concrete, have three-dimensional structures that are more significant at a small scale, which cause sunlit, shaded, or half sunlit leaves under dissimilar illuminations. The higher variability of leaf surface temperatures combined with the complexity in the leaf structure induces the more oscillated intensity of thermal anisotropy. Fig. 6c shows that over grasses, the DRTs are asymmetrically distributed from the zenith angle of −60° to +60°, with the DRTs in the southern observations slightly higher than in the northern ones, which indicate that a slight hotspot effect appears.
5. Validations of the Thermal Inertia Model

It has been reported that soil thermal inertia can be validated by soil property (Murray & Verhoef, 2007a, 2007b) or by measured soil heat fluxes and surface temperatures (Wang et al., 2010). However, it is difficult to know the “true” thermal inertia over highly heterogeneous urban regions and then to compare the “true” value with that derived from remote sensing at a coarse spatial resolution. Regarding the link between thermal inertia and the diurnal LST cycle, Sobrino and El Kharraz (1999a, 1999b) proposed that the accuracy of thermal inertia could be determined by comparing the measured and predicted LST indirectly. In this study, similar procedures were conducted to validate the presented NLS technique. The accuracy assessments of thermal inertia over the scale model in general are presented in Fig. 7.

The validation results provided in Fig. 7 indicate that the accuracy of the thermal inertia inverted from temporal DRTs by the NLS technique reaches an acceptable level. With zenith $\in [-60^\circ, +60^\circ]$ and azimuth $\in [0^\circ, 360^\circ]$, the temperature RMSE (root mean square error) ranges from 0.62 to 1.47 K. The RMSE increases to its maximum in the southeastern observations because the DRTs in those measurements ascend to the maximum values right at mid-morning, which invalidates the default acknowledgement just subsequent to solar noon when the diurnal LST reaches its peak.

5.1. Inter-comparison between methods

The inter-comparison offers a clearer observation among methods. The NLS is compared with two well-known methods, including the X&C by Xue and Cracknell (1995), and the FTA (Four Temperatures Algorithm) by Sobrino and El Kharraz (1999a). These three methods (i.e., X&C, FTA, and NLS) are examined at four observation angles: A ($55^\circ$, $45^\circ$), B ($55^\circ$, $135^\circ$), C ($55^\circ$, $225^\circ$), and D ($55^\circ$, $315^\circ$). To implement FTA, temperature gaps are chosen at 01:00, 07:00, 13:00, and 19:00. The inter-comparison among these three is given in Table 3.

We confirm the conclusion from Table 3 that all three methods are capable in practical utilization. In spite of the common capability, these methods behave distinctively in several cases. With the average RMSEs of 1.16, 1.53, and 2.26 K for NLS, FTA, and X&C, respectively, the accuracy with an order from highest to lowest RMSE is NLS $>$ FTA $>$ X&C. The X&C uses only two temperature observations in addition to the moment of the maximum temperature. The FTA explores the combination of four temperature observations. The NLS provides an unbiased estimation of thermal inertia by nonlinear optimization and utilizes all temperature observations that are available as inputs to derive thermal inertia. It does not require the temperature observation at a specific moment, which is required in X&C and FTA. The inter-comparison between these methods not only proves the effectiveness of NLS but also illustrates the advantages of NLS on thermal inertia estimation by as many LST observations as possible.

5.2. Sensitivity analysis

In studies such as Cai et al. (2007) and Sobrino and El Kharraz (1999a), sensitivity analyses of thermal inertia on parameters such as albedo and diurnal temperature variation were made. This work,

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<th>Methods</th>
<th>RMSE (K)</th>
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<td>A ($55^\circ$, $45^\circ$)</td>
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<tr>
<td>NLS</td>
<td>1.10</td>
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<td>FTA</td>
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however, focuses on DTI intensity (represented by \( I_{\text{DTI}} \) or \( R_{\text{DTI}} \)). Parameters including albedo (\( \alpha \)) and DRT are therefore reinvestigated.

According to Eq. (5), the arguments that need examination are the albedo (\( \delta \alpha \), \( \delta \alpha \) is the increment in sensitivity analysis), which is linearly related to thermal inertia, and the observed DRT vector (\( \delta \mathbf{T} \)). The dependent variable can be either \( I_{\text{DTI}} \) or \( R_{\text{DTI}} \). The interval of \( \delta \alpha \) is set as \([0, 0.25]\). It is somewhat complex to set the interval of \( \delta \mathbf{T} \) because this interval represents a vector of parameters, and it is unreasonable if the elements in \( \delta \mathbf{T} \) are all added by a consistent increment. A set of random increments is thus produced, where \( \delta \alpha \) and \( \delta \mathbf{T} \) are all added by a consistent increment (the uniform distribution is utilized hereafter) in the interval of \([0, 5]\). The \( \delta I_{\text{DTI}} \) and \( \delta R_{\text{DTI}} \) along with \( \delta \alpha \) and \( \delta \mathbf{T} \) are demonstrated in Fig. 8. The results show that if \( \delta \alpha \in [0, 0.25] \) and \( \delta \mathbf{T} \in [0, 5] \), we obtain \( \delta I_{\text{DTI}} \in [-100, 1100] \) [in TIU] and \( \delta R_{\text{DTI}} \in [-0.11, 0.56] \).

There are noticeable similarities between \( I_{\text{DTI}} \) and \( R_{\text{DTI}} \) regarding the sensitivity analysis: (1) A higher \( \delta \mathbf{T} \) produces a higher \( \delta I_{\text{DTI}} \) and \( \delta R_{\text{DTI}} \). (2) The higher (Area B in Fig. 8) and lower (Area A) values in general are separately distributed. (3) With a fixed \( \delta \mathbf{T} \), \( \delta R_{\text{DTI}} \) remains principally unchanged with the increase of \( \delta \alpha \) (Fig. 8b). In contrast, \( \delta I_{\text{DTI}} \) is monotonically increasingly related to \( \delta \alpha \), indicating that a higher \( \delta \alpha \) always leads to a higher \( \delta I_{\text{DTI}} \) (Fig. 8a). The theoretical investigation for this inverse relationship is provided in Appendix A. Eq. (13) provides the explanation for why the dividing line between Area A and B in Fig. 8a is inclined, corresponding to a horizontal line in Fig. 8b. Practically speaking, the \( R_{\text{DTI}} \)'s insensitivity to albedo facilitates simplifying the albedo estimation because urban albedo slightly changes during diurnal cycles (Sailor & Fan, 2002). The accuracies of the chosen thermal sensors are higher than 1 K; therefore, the results shown in Fig. 8 reveal that the assessment of DTI intensity is insensitive to \( \delta \mathbf{T} \) when \( \delta \mathbf{T} \in [0, 1] \).

### 6. Directional thermal inertia

The spatial distribution of DATI and DTI along with observation angles over the scale model, flat concretes and grasses is investigated.

#### 6.1. Scale model

On the basis of the DRT polarization data, the NLS technique is carried out to estimate the DATI and DTI over the scale model, and the results are demonstrated in Fig. 9.

The \( I_{\text{DATI}} \) and \( R_{\text{DATI}} \) in Fig. 9a are 0.01 K\(^{-1}\) and 1.36, respectively. DATI greatly fluctuates along with the observation angle. The assessments in the southwestern observations have lower intensities, and the highest intensities appear in the northeastern direction. With \( I_{\text{DATI}} \) and \( R_{\text{DATI}} \) of 1440 TIU and 1.94, respectively, a comparable distribution of DTI is acquired in Fig. 9b. The extreme DTIs are primarily in the southwest and southeast (the lowest) directions, and in the north and northwest (the highest) direction. The nonlinear conversion between DATI and DAI may lead to this inconsistency. During the typical summertime at the mid-latitudes of the northern part of the globe, south-oriented walls have higher temperature fluctuations than north-oriented walls throughout the diurnal cycle; therefore, there are lower DATIs and DTIs in the southern semi-sphere than in the northern semi-sphere.

As shown, the DTI in Fig. 9b lies between 1530 and 2970 TIU. Sugawara et al. (2001) reviewed previous studies on the estimation of the square of urban thermal inertia (i.e., \( P^2 = \rho c \lambda \)) and found that the \( P^2 \) of concrete ranges from \( 0.57 \times 10^6 \) to \( 5.51 \times 10^6 \) TIU\(^2\), which means \( P \) varies from 755 to 2350 TIU. The estimated thermal inertia herein is slightly higher than that referred to in Sugawara et al. (2001), which is consistent with the findings of the present study.

![Fig. 8](image1.png)

**Fig. 8.** The estimation errors of the DTI intensity induced by errors of the albedo and DRT. (a) and (b) represent \( I_{\text{DTI}} \) and \( R_{\text{DTI}} \), respectively.

![Fig. 9](image2.png)

**Fig. 9.** The spatial distribution of DATI and DTI over the scale model. (a) DATI \( (I_{\text{DATI}}=0.01 \text{ K}^{-1}; \ R_{\text{DATI}}=1.36) \), and (b) DTI \( (I_{\text{DTI}}=1440 \text{ TIU}; \ R_{\text{DTI}}=1.94) \).
6.2. Flat surfaces

The distributions of directional inertia of flat surfaces with increasing zeniths (from north to south) are presented in Fig. 10. As shown in Fig. 10a, even with flat concrete, the estimated thermal inertia is anisotropic, ranging from 2243 to 2557 TIU. The DTI, in general, is lower when the zenith is lower. The DTI results are approximately symmetrical at a zenith of 0° (see Fig. 10a) because there is no shaded component, and the micro-structure of the concrete itself, combined with the FOV effect, becomes the driving factor that controls thermal anisotropy. We do not provide the thermal inertia of pure concrete as a reference to the estimated DTI because the former represents the thermal property of a homogeneous material but the latter is a measure of thermal inertia of several heterogeneous layers together. The layer of surface concrete in this study is thin and there were studies indicating that the thermal inertia of layered materials does not appear the same as that of a large mass of homogeneous material (Byrne & Davis, 1988; Goward, 1981).

The averaged grass thermal inertia at zeniths between −30° and +30° is 2032 TIU (Fig. 10b). Sobrino and El Kharraz (1999a, 1999b) reported a typical assessment of grass thermal inertia of approximately 2100 TIU, nearly identical to the estimated value herein, although we recognize that the grass type and soil moisture status underneath are both considerable factors that affect thermal inertia. For grass, a higher zenith always induces a higher DTI. However, the DTI is asymmetrically distributed at a zenith of 0°, with the northern DTI slightly higher than the southern DTI. This asymmetrical bias is due to the slight hotspot effect over grass, which renders the varying amplitude of diurnal LST.

Thermal inertia of flat surfaces can also be estimated by the night cooling method (NCM), which requires a clear-sky night when there are little sensible and latent flux, given by (Verhoef, 2004):

\[ P_{nc} = \frac{2(R_n \sqrt{\Delta})}{(\Delta T_s \sqrt{\pi})} \]  

where \( P_{nc} \) is the thermal inertia estimated using NCM; \( R_n \) is the net radiation (unit: Wm\(^{-2}\)); and \( \Delta T \) (unit: s) and \( \Delta T_s \) (unit: K) are the time and surface temperature differences between sunset and sunrise. The estimated thermal inertia of concrete and grass are shown in Table 4. The thermal inertia of concrete by UCM is 259.8 TIU lower than the averaged thermal inertia by NLS, and the thermal inertia of grass by NCM is 506.8 TIU higher than the averaged thermal inertia by NLS. The difference of estimated thermal inertia between NCM and NLS over grass is higher than that over concrete, this is because the grass exhibits thermal anisotropy and thus affects the estimation of thermal inertia and it is difficult to choose a representative thermal inertia in a range from 1911.8 to 3234.0 TIU. We do not expect the thermal inertia estimated using these two methods to be identical because over urban areas, it is difficult to define the accurate time of sunset and sunrise since there is a significantly long period when the sun is above the horizon but the sunlight is shaded by adjacent buildings.

7. Discussions

The aforementioned results indicate that urban thermal inertia causes significant impacts on the remote estimation of thermal inertia. Three issues are further discussed: (1) How does the geometry of the urban scale model (denoted by street width and construction ratio) affect DTI intensity? (2) What is the relationship between the DTI intensity and DRT intensity (IDRT)? IDRT is designated as the maximum difference among DRTs in a certain moment during a diurnal cycle. (3) Finally, we provide discussions about how the results of the scale model relate to those in a real urban environment.

7.1. Relation between DTI intensity and street width

The impact of urban geometry on DTI intensity is investigated in this section. The geometry of the scale model, represented by street width, is one of the causes of thermal anisotropy and is thus the cause of the anisotropic estimation of thermal inertia. In practice, and for simplicity, \( R_{DRTI} \) is chosen here to represent the DTI intensity. Two parameters, \( R_{DRTI} \) and \( R_{CC} \) (construction coverage ratio, CCR), are estimated by varying the street width. The results are presented in Fig. 11.

As shown in Fig. 11a, \( R_{CC} \) decreases with growing street width. This response is expected because the construction becomes denser when the street width decreases. At the beginning of the growth of the street width, \( R_{DRTI} \) increases rapidly (see Fig. 11b); it remains at

<table>
<thead>
<tr>
<th>Surface Type</th>
<th>( R_n ) (Wm(^{-2}))</th>
<th>( \Delta T ) (s)</th>
<th>( \Delta T_s ) (K)</th>
<th>( P_{nc} ) (TIU)</th>
<th>DTI (TIU)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concrete</td>
<td>111.6</td>
<td>42200</td>
<td>12.3</td>
<td>2131.4</td>
<td>2243.0–2557.5</td>
</tr>
<tr>
<td>Grass</td>
<td>96.3</td>
<td>42200</td>
<td>7.9</td>
<td>2863.3</td>
<td>1911.8–3234.0</td>
</tr>
</tbody>
</table>
a high level when \( d_{E-W} \) lies between 12 and 28 m; but \( R_{DTI} \) shrinks when \( d_{E-W} \) is higher than 28 m. If \( R_{CC} \) is close to 0 or 1, which means the scale model appearing in the FOV scope would be nearly flat ground or roofs, a lower \( R_{DTI} \) is reasonable due to the lower urban heterogeneity. However, if \( R_{CC} \) has a medium value between 0 and 1, which means the construction and ground are distributed in balance, a higher \( R_{DTI} \) would be caused by strong thermal anisotropy. The conclusion is that \( R_{CC} \) over the scale model is a parameter that could be used to predict the DTI intensity.

### 7.2. Relation between DTI intensity and \( I_{DRT} \)

A statistical analysis regarding the connection between \( R_{DTI} \) and \( I_{DRT} \) is provided. The scale model is rearranged with varying block distances arranged east–west and south–north: (1) \( d_{S-N} = 16 \) m, \( d_{E-W} = 6.4 \) m; (2) \( d_{S-N} = 12 \) m, \( d_{E-W} = 4.8 \) m; (3) \( d_{S-N} = 8 \) m, \( d_{E-W} = 3.2 \) m. The statistical procedures are as follows. (1) Fix either the azimuth or zenith, and build a fixed profile. (2) On the produced profile, the relationship between \( R_{DTI} \) and \( I_{DRT} \) is investigated. The results are shown in Fig. 12.

As shown in Fig. 12, \( R_{DTI} \) has an approximate linear relation with \( I_{DRT} \). The results of the fitting of \( R^2 \) by the profiles of the fixed azimuth are 0.63, 0.46, and 0.79 for the different distances among the building blocks while these values increase to 0.98, 0.98, and 0.9958 by the profiles of the fixed zenith. These results show that the relationship between \( R_{DTI} \) and \( I_{DRT} \) by the fixed azimuth is not as close as that by the fixed zenith because both DRT and DTI are more azimuth-dependent, which means that azimuth rather than the solar zenith is the more significant parameter governing physical phenomena such as the component status and hotspot effect. For the scale model, it is further indicated in Fig. 12 that \( R_{DTI} \) has an approximate linear correlation with \( I_{DRT} \), given as:

\[
R_{DTI} \approx 0.1 I_{DRT} + 1.0
\]

where \( I_{DRT} \) is the DRT intensity. The relationship between \( I_{DRT} \) and \( R_{DTI} \) remains unchanged with the varying geometry of the scale model, which implies that over the scale model, \( I_{DRT} \) is a good indicator to predict \( R_{DTI} \).

### 7.3. Indication of scale model relating to real urban environment

The DTI results shown in Figs. 9 and 10, combined with the discussions using \( R_{CC} \) and \( I_{DRT} \) as indicators of DTI intensity (see Figs. 11 and 12), have been primarily tested by the scale model and flat surfaces. However, a real urban environment is far more complex, being characterized by irregular building heights and various construction materials and land covers. In a real world environment, we conclude the following:

**P1:** The thermal anisotropy of real urban surfaces has a significant impact on estimates of urban thermal inertia due to the even higher urban heterogeneity.

**P2:** Although \( R_{CC} \) can be a predictor for DTI intensity over the scale model, we recognize that designing a surface parameter that is more capable of quantifying the extent of urban heterogeneity will be better than \( R_{CC} \).

**P3:** The approximate linear relation between \( I_{DRT} \) and \( R_{DTI} \) is still valid in a real environment.

It is difficult in a real urban environment to define a reasonable component, then to calculate the component fraction and thermal anisotropy, and thus to estimate the DTI. To support \( R_{DTI} \) in a real environment, we provide the theoretical explanation given in Appendix B.

The positive linear relationship between the intensities of DRT and DTI indicates that using temporal surface temperatures during nighttime would be better than during daytime to estimate remotely sensed urban thermal inertia because the DRT intensity during nighttime is much lower. This corresponds with previous studies such as Ten Berge and Stroosnijder (1987) and Verhoef (2004), which also stressed that thermal inertia dominates the surface thermal behavior at night when sensible and latent heat fluxes are small. The significant DTI intensity induced by using DRT as a parameter for the thermal inertia estimation indicates that the “estimated” DTI should be rectified before being used as an input in the urban SEB model. This necessity becomes more apparent when using satellite thermal images of a wide swath. The DTI intensity has been estimated in this work, but more difficult is the definition and estimation of the “true” urban thermal inertia in a coarse-resolution pixel, as urban thermal inertia at the pixel-scale is a nonlinear aggregation of component thermal inertia (Goward, 1981). As indicated by Voogt and Oke (1997, 1998b), the urban LST at the pixel-scale is also a conceptual aggregation of component temperatures. The complete urban surface temperature was thus defined as a better representation of surface-atmosphere interactions (Voogt & Oke, 1997). From the SEB perspective, we recommend that a complete urban surface temperature instead of DRT be used to estimate the urban thermal inertia. Paradoxically, these thermal inertia “definitions” relate to physical property, surface geometry, and external environment; this is quite natural because the definition of LST itself at the pixel-scale currently is debatable (Li et al., 1999).

### 8. Conclusions

This study focuses on assessing the impacts of urban thermal anisotropy on the remote estimation of thermal inertia. In essence, this research explores diurnal thermal anisotropy over urban areas because...
thermal inertia is a parameter that is closely related to the diurnal amplitude of LST variation.

As a case study, a scale model that is downscaled from real urban environments is constructed. We pay further attention to flat concrete and grasses. To estimate thermal inertia, the NLS technique is proposed to give a more compromising estimation using temporal LST measurements. Indirect validation by predicting LSTs is conducted, and the results indicate that the NLS technique is well-behaved, with prediction errors ranging from 0.62 to 1.47 K. The DATI and DTI over the scale model show strong anisotropic effects. When zenith $\in [-60^\circ, +60^\circ]$ and azimuth $\in [0^\circ, +360^\circ]$, we obtain \(\text{DATI} = [0.028, 0.038] \) (in K$^{-1}$) and \(\text{DTI} = [1530, 2970] \) (in TIU). The DTI of flat concrete and grasses exhibits similar anisotropic effects as that of the scale model. Further discussions about the relation between DTI intensity and other factors indicate that \(I_{\text{ORT}}\) has the potential to become an indirect parameter for predicting DTI intensity.

Although progress has been made, problems remain. (1) Most assessments are made in clear-sky days. (2) In real environments, we may face urban surfaces of greater complexity than the scale model designed. Even so, this study provides a detailed and new perspective about how and how much thermal anisotropy affects the remote estimates of urban thermal inertia.

Acknowledgments

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Fig. 12. The relationship between \(R_{\text{ORT}}\) and \(I_{\text{ORT}}\). (a), (c), and (e) are the representatives of the fixed azimuth; and (b), (d), and (f) denote those of the fixed zenith.
We also express our gratitude to the anonymous reviewers who gave us insightful comments on improving this study.

Appendix A. Theoretical sensitivity analysis of Albedo on DTI intensity

Only regarding the first term of Fourier series, thermal inertia is expressed by (Xue & Cracknell, 1995):

$$P = \frac{(1 - \alpha)}{\Delta T} C_2 = C (1 - \alpha)$$ (11)

where P and \( \alpha \) are thermal inertia and albedo; C1 and C2 are the simplified coefficients; and C is a combined representation, given as \( \frac{C}{\Delta T} \).

The intensity of DTI (\( R_{DTI} \) and \( R_{DTI}^0 \)) can then be given as:

$$\frac{I_{DTI}}{R_{DTI}} = \frac{P_{max} - P_{min}}{P_{min} - \min} = \frac{C_{max} (1 - \alpha) - C_{min} (1 - \alpha)}{C_{min} (1 - \alpha)} = \frac{C_{max}}{C_{min}}$$ (12)

where the subscripts of 'max' and 'min' denote the observation angle where the thermal inertia reaches the maximum and minimum values. We thus obtain the partial differential of \( I_{DTI} \) and \( R_{DTI} \) on albedo \( \alpha \) alone as:

$$\frac{\partial I_{DTI}}{\partial \alpha} = C_{min} - C_{max}$$

$$\frac{\partial R_{DTI}}{\partial \alpha} = 0$$ (13)

Although the above deductions are not strict, Eq. (13) indicates that \( \partial I_{DTI} \) (i.e., \( \partial R_{DTI} \)), to some degree, is linearly dependent on albedo, while \( \partial R_{DTI} \) (i.e., \( \partial R_{DTI} \)) is independent of albedo.

Appendix B. Deduction of the Theoretical Relationship between \( I_{DTI} \) and \( R_{DTI} \)

The DRT intensity is estimated by (Lagouarde et al., 2010):

$$I_{DTI} = T(t_{max}, \Phi) - T(t_{max}, \Phi)$$ (14)

where \( t_{max} \) represents the moment when \( I_{DTI} \) reaches the maximum, typically at the moment subsequent to solar noon; \( \Phi \) and \( \Phi \) are the two observation angles where the highest and lowest DRTs appear.

During a diurnal cycle, the minimum LST difference among components compared with \( I_{DTI} \) is tiny (Zhou, 2010) so that:

$$T(t_{min}, \Phi) \approx T(t_{max}, \Phi)$$ (15)

where \( t_{min} \) often resides at the moment prior to sunrise in a clear-sky day. Because the amplitude of diurnal temperature variation (\( \Delta T \)) usually connects the thermal inertia \( P \) by a certain function \( f(\Delta T = f(P)) \), further deduction is as follows:

$$I_{DTI} = T(t_{max}, \Phi) - T(t_{max}, \Phi) = T(t_{min}, \Phi)$$

$$= [T(t_{max}, \Phi) - T(t_{min}, \Phi)] - [T(t_{min}, \Phi) - T(t_{min}, \Phi)]$$

$$= \Delta T(\Phi) \approx \Delta T(\Phi)$$

$$\approx f(P(\Phi)) - f(P(\Phi)) = \frac{P(\Phi)}{f(P(\Phi))}$$ (16)

Assuming \( \kappa = \frac{P(\Phi)}{f(P(\Phi))} \), we obtain from Eq. (16):

$$\Rightarrow P(\Phi) = f(P(\Phi)) - f(P(\Phi)) \frac{I_{DTI}}{R_{DTI} \approx 1}$$

$$\Rightarrow P(\Phi) = \frac{P(\Phi)}{f[P(\Phi)]}$$

$$\Rightarrow R_{DTI} = \frac{I_{DTI}}{P(\Phi)} \cdot \frac{I_{DTI}}{1}$$

Note that \( \kappa \) is the slope of the line determined by two points \( (P(\Phi), f(P(\Phi))) \) and \( (P(\Phi), f(P(\Phi))) \) in feature space. We propose the relationship between \( R_{DTI} \) and \( I_{DTI} \) represented by Eq. (17) in a real urban environment under clear-sky conditions is basically reasonable. Eq. (17) has a similar expression with Eq. (10), and it offers a rapid way to predict \( R_{DTI} \) through \( I_{DTI} \).

References


