Spatial variability of air temperature and appropriate resolution for satellite-derived air temperature estimation

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Spatial variability of air temperature and appropriate resolution for satellite-derived air temperature estimation

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This study investigates the spatial variability of air temperature over Hong Kong using in situ air temperature recorded from a mobile traverse combined with an ASTER thermal satellite image. Three different degrees of urbanization in Hong Kong, including city downtown (Kowloon), suburban areas (Yuen Long and Shatin), and rural countryside (Tai Mo Shan and Lam Tsuen) are analysed. The spatially variable relationship between air and surface temperature was evaluated using two spatial averaging techniques, namely spatial resampling and buffering around air temperature points. The strength of the correlation coefficient was tested for every decreasing resolution and the appropriate spatial scales of air temperature in urban, suburban and rural areas were found to be 200 m, 450 m and 700 m, respectively. The differences in the spatial scales of air temperature in these regions are attributed mainly to structural factors of land cover such as city block size, building density and percentage of green areas, and secondarily to the climatic conditions being operating in, and which commonly typify these individual regions. Thus small scale lengths in the urban area corresponded to heterogeneous land cover, a well developed urban boundary layer, low wind speeds and a low lapse rate, whereas longer scale lengths were observed in suburban and rural areas having more homogeneous land cover, higher wind speeds and higher lapse rate.

1. Introduction

Air temperature ($T_a$) is a key parameter for describing the energy balance and energy fluxes of the earth and is a key determinant of human comfort and plant growth. Its measurement over space however is usually limited to fixed meteorological stations which do not provide spatially continuous data. This is a particular problem for cities with a complex pattern of land cover, where air temperature may be much more variable spatially than can be interpolated from a network of ground stations. However, a number of studies have been able to obtain spatially continuous land surface temperature ($T_s$) covering whole cities from remote sensing platforms. These include airborne multispectral scanners (Asrar et al. 1988, Holbo and Luvall 1989, Ben-Dor and Saaroni 1997), the NOAA AVHRR satellite series (Platt and Prata 1993, Johnson et al. 1993, Prata 1994, Vazquez et al. 1997), MODIS (Wan, 1999, Jacob et al. 2004), Landsat TM (Honjo and Takakura 1987, Kawashima et al. 2000), and Terra ASTER (Yamaguchi et al. 1998, Nichol 2005). Based on the premise that surface temperature is a major determinant of air

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temperature, a number of studies have established a strong or significant relationship between satellite-derived $T_s$ and $T_a$, but few have done so over complex urban and suburban regions, and none have done so using extensive in situ air temperatures collected at the image time.

In particular, Stoll and Brazel (1992) and Spronken-Smith and Oke (1998) noted the difficulty of correlating point-derived air temperatures with image pixels, especially in complex terrain. Prata (1994) was able to establish a strong relationship between $T_a$ and satellite-derived $T_s$ from NOAA AVHRR images by averaging a series of contact surface temperatures collected over a homogeneous site corresponding in size to an image pixel, and Kawashima et al. (2000) obtained a higher correlation between air temperature and spatially averaged surface temperatures, than for single pixels corresponding to single ground points. These studies suggest that a strong relationship between satellite-derived surface and ambient air temperature can be obtained provided the scales of data collection are appropriate in that the resolution of surface temperature matches the scale of variation in air temperature. Since most previous studies (Kawashima et al. 2000, Colombi et al. 2007) have been confined to the examination of regional scale air temperature using fixed stations sparsely distributed over large regions, e.g. 35,000 km$^2$ (Colombi et al. 2007) and 40,000 km$^2$ (Kawashima et al. 2000) they have been unable to confirm the suitability of satellite-derived surface temperature for urban heat island analysis or to recommend the resolutions at which satellite-derived surface temperature represents air temperature over a city and its hinterland. While several studies have examined the relationship between surface and air temperature, only a few have examined the scale of air temperature variation. These have all been regional scale studies using limited data from ground points, and they have not examined a variety of land cover types.

In order to use satellite-derived $T_s$ as a surrogate for $T_a$, the scale of spatial variation of air temperature and its optimum scale of correlation with surface temperature must be determined. The present study was carried out in Hong Kong, a modern city with a range of degrees of urbanization, from the densely built-up central business, commercial and residential districts, and newly developed satellite towns, to low density suburban areas and undeveloped countryside. The study examines the spatial variability of air temperature corresponding to different degrees of urbanization over Hong Kong on a winter night.

2. Study area and data used

In this study, increasingly urbanized land cover is represented by five districts. These include the densely urbanized Kowloon Peninsula, which is low lying, mainly flat terrain; two new satellite towns of Shatin and Yuen Long in the New Territories, representing suburban areas as they are less densely developed than Kowloon, and two rural areas which include the mountainous region of Tai Mo Shan and a less rugged section of Lam Tsuen country park, both in the New Territories (figure 1). Like many sub-tropical cities, Hong Kong is thermally uncomfortable for several months of the year, which is exacerbated by a lack of urban green space, congestion and high anthropogenic energy inputs.

An ASTER level 1B image was acquired from NASA Jet Propulsion Laboratory and ASTER GDS Japan on 31 January 2007 (22:42 local time). This is the first night-time ASTER image which covers almost the whole of Hong Kong including Kowloon and the New Territories. Five thermal bands from (8.125 μm
to 11.65 μm) were obtained but the visible and SWIR bands were not available during night-time.

*In situ* air temperature measurements were taken at the same time as the ASTER overpass from two mobile vehicles driven around Kowloon Peninsula and New Territories within 2 h of the image time. The routes passed through the five study regions: urban (Kowloon), suburban (Yuen Long and Shatin) and rural (Tai Mo Shan and Lam Tsuen) (figure 1) and the total length was 130 km. The vehicles were deployed with temperature sensors (an IAQ Calc thermistor and a thermocouple) and Global Positioning System (GPS) receiver (figure 2). The sampling frequency of temperature sensors was one second, and air temperature records were obtained nearly every 22 m. The resolutions of all temperature sensors are 0.1 °C. In order to accurately estimate the *in situ* measurements at the precise image time, the mobile measurements were normalized to the image time, 10.42pm using data from climate stations. A thermal inversion was recorded during the mobile traverse at approximately 600 m elevation on Tai Mo Shan mountain, as air temperature rose from c.11.1 °C near sea level to 12.1 °C on the mountain top at 900 m.

3. **Image processing**

3.1 **Orthorectification**

Image orthorectification to the Hong Kong 1980 grid coordinate system was performed using the Rational Function Model (Tao and Hu 2000) and a 10 m resolution DEM. A total of 30 ground control points were selected from high

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Figure 1. Mobile traverse route across the five districts.
contrast features on 1:1000 scale digital base maps and the seventh order rational function coefficient derived from these gave an overall rms of c.0.45 pixel.

3.2 Spectral radiance to surface temperature \((T_s)\)

First the ASTER image was converted from radiance-at-sensor to brightness temperature \((T_b)\) using the Planck function (Jensen 2000). Secondly the image was corrected for emissivity differences using the emissivity modulation method of resolution enhancement (Nichol in press) using equation (1) resulting from the Stefan-Bolzman law. The method is able to obtain a more significant correlation between fixed ground measurements for the resolution-enhanced image following emissivity correction, than for the same image at nominal resolution. Using this method, in order to correct for emissivity differences due to different land cover types, a land cover map at 10 m resolution was derived from a SPOT5 image using supervised classification. Six broad land cover classes, namely forest, water, grassland, shrubland, urban and soil/sand were identified. Corrections for emissivity differences were then carried out according to land cover type by ratioing the \(T_b\) image with the classified image from a land cover map in which the pixel values for the land cover class were replaced with the corresponding emissivity value (Nichol 1994, 1996) (equation (1); see Sabins 1997). The emissivity-corrected image having a pixel size of 10 m is shown in figure 3.

\[
T_s = T_b / \varepsilon^{1/4}
\]  

Only band 13 (10.25–10.95 \(\mu\)m) was selected for further analysis, as visual inspection indicated that it contained less stripe noise, and the wavelengths are least subject to atmospheric effects including ozone absorption (Gillespie et al. 1999).

4. Methods

The emissivity-corrected \(T_s\) image at 10 m resolution was compared with \(T_a\) from mobile measurements. In order to investigate the spatial variability of \(T_a\) in relation...
to $T_s$, the $T_s$ values were spatially averaged at increasing distances from the $T_a$ points by two methods:

i. Application of a buffering technique to average the pixel values surrounded by each point along the mobile traverse at increasing distances from 10 to 700 m, and the average $T_s$ value within the buffers was regressed against the $T_a$ point.

ii. Degrading the spatial resolution by spatial resampling of the image pixels using kernels of increasing size from 10 to 700 m; the average $T_s$ value within each kernel size was regressed against the average values of all the air temperature points falling within that sized kernel.

In order to ensure sufficient data for calculating the correlation coefficient, the maximum resampling kernel/buffer size in the spatially restricted urban and suburban areas was 700 m, giving 14 data observations for the smallest district. Buffering tests the $T_a/T_s$ relationship around single points, whereas spatial resampling tests for all the points within each sized kernel. Thus if, when a certain kernel size is reached, the $T_s$ points are no longer spatially autocorrelated due to increasing heterogeneity of surfaces within the kernel, the correlation with air temperature

Figure 3. Emissivity-corrected $T_s$ image at 10 m resolution. The key shows temperatures in °C.
temperature should fall. The correlation would also fall if averaging of the surface temperatures became too generalized to represent the spatial variations in air temperature. With buffering, if the surface is the main influence on air temperature the correlation would be expected to decrease with increasing distance from the air temperature points as the nearby surface became less influential on the point. However, the correlation may even increase with increasing distance if factors operating at regional, as opposed to local scale were present, and this is likely as the buffer size approaches the size of the dominant local air mass. For the purposes of this study local scale factors refer to the size of areas affected by small scale turbulence, i.e. up to 100 m as defined by Oke (1987), and regional scale factors operate at the scale of a whole city (Oke 1988). Suburban areas are defined as areas of lower density development surrounding a city, and having large green space fractions (Arnfield 2003).

In order to test the validity of the correlations at the observed optimum scale lengths, the image was converted to satellite-derived air temperature using the corresponding regression equations for urban, suburban and rural areas individually (table 1), and validated against in situ air temperature derived from the mobile traverse points.

5. Results

The spatial scales of air temperature variation indicated by the spatial averaging appear to be in the region of 200 m (figure 4(a)), 450 m (figure 4(b)) and 700 m (figure 4(c)) for urban, suburban and rural areas respectively, indicated by the peak correlations at these distances. For urban areas the peak at 200 m followed by a decline with increasing distance may be due to the strong influence of the local surface since building blocks and street divisions are at approximately this length. Although the buffering technique also indicates a peak in correlation at the 200 m local scale for urban areas (figure 4(d)), the correlations continue to increase slightly thereafter. This is thought to be due to a dual influence on near surface air temperatures operating on a winter night, when cooling is induced by two major heat sinks, namely the adjacent urban surface operating at micrometeorological scale within the urban canopy layer, and the upper cold air mass operating at the broad regional scale of the urban boundary layer. Thus, as postulated above (§4), the correlation increases with increasing distance because factors operating at regional (i.e. city scale), as opposed to local scales are present.

Correlations for the rural areas appear to increase more markedly with increasing distance than for urban areas, showing less local influence. The highest correlation shown by resampling (at 700 m) (figure 4(c)) indicates that microscale patterns of

<table>
<thead>
<tr>
<th>MAD (°C)</th>
<th>Within regions</th>
<th>Entire image</th>
<th>Correlation (r)</th>
<th>Equations ($y: T_a$, $x: T_s$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban (@200 m)</td>
<td>0.339</td>
<td>2.547</td>
<td>0.65†</td>
<td>$y=11.626 + (0.358 \times x)$</td>
</tr>
<tr>
<td>Suburban (@450 m)</td>
<td>0.784</td>
<td>1.861</td>
<td>~0.55†</td>
<td>$y=11.399 + (0.184 \times x)$</td>
</tr>
<tr>
<td>Rural (@700 m)</td>
<td>0.525</td>
<td>1.349</td>
<td>~0.8†</td>
<td>$y=3.277 + (0.762 \times x)$</td>
</tr>
</tbody>
</table>

† Correlation is significant at the 0.01 level (2-tailed).
surface temperature are much less influential than in the urban area. Furthermore, the relationship between air and surface temperatures appears stronger in the rural area, with a correlation coefficient above 0.80 at the optimum length scale for both resampling and buffering, compared with $r=0.60–0.65$ for urban. This is probably due to the much lower frequency of $T_s$ variation in rural areas, due to more homogeneous land cover, and thus a more direct correspondence with the adjacent air temperature. Additionally, vegetative surfaces, which predominate in rural areas, are recognized as good indicators of air temperature (Kawashima et al. 2000) and have even been used as a surrogate for air temperature (Prihodko and Goward 1997), i.e. a correlation coefficient near to 1 may be expected. The high correlation coefficient approaching 0.9 for rural areas (figures 4(c) and 4(d)) would appear to support this. In suburban areas the optimum length scale of $c.450$ m lies between that of urban and rural areas, but the correlation coefficient of 0.55 is the lowest. Furthermore, conversion of the image-derived $T_s$ to $T_a$ using the regression equation derived from the whole image obtained a much lower mean absolute difference (MAD) when compared with mobile traverse data than when the regression equations for each individual land cover type were used (table 1).
6. Discussion

The results suggest that the scales of variation in air temperature become smaller with increase in building density and decrease of green areas. For example, green areas and building density in suburban areas are intermediate between rural and fully urbanized areas (table 2), and the suburban traverse route alternates between vegetated and built-up land cover types, which have distinctly different heat flux characteristics. Thus it may be suggested that the observed optimum scale of c.450 m² represents a critical size at which vegetated or built land cover types affect air temperature. For example a patch of vegetation requires a minimum size of 450 m² to have a cooling effect and built areas of over 450 m² may induce urban heat island formation. Indeed it was noted that in urban areas, small green spaces such as grassy pitches or small treed parks of c.1 hectare (100 m²) in size produced significantly lowered surface temperatures, but these did not appear to influence air temperatures along the traverse route.

The peak correlation at c.200 m in urban areas corresponding to the scale lengths of building blocks and street divisions is probably more influenced by anthropogenic heat discharged from commercial, industrial and domestic electricity usages, and vehicles. Atkinson (2003) noted that in London anthropogenic heat was the most significant factor, accounting for approximately 40% of the urban heat island anomaly at night, as against other less important factors, namely sky view factor, thermal inertia, albedo, roughness length and surface resistance to evaporation. Furthermore, wind speed at the image time was less than 1 ms⁻¹ in the urban area (table 2), thus the low horizontal air movement coupled with low vertical energy exchange due to the inversion would reinforce the effects of the anthropogenically influenced microscale surface morphology at 200 m scale, on air temperature. The repetition of this local pattern throughout the urban area produces the continued slight upward trend in the correlations over the larger buffering distances following the steep increase up to 200 m (figure 4(d)). The downward trend in spatial resampling above 200 m (figure 4(a)), however, may indicate intra-urban differences at meso-scale between different district types, e.g. residential, industrial, commercial and green areas. Thus nearby air temperature points within the same resampling kernel are no longer autocorrelated if they belong to a different urban sub-type, although air temperature within each major urban sub-type is correlated with surface temperature at the scale of 200 m.

Table 2. Land cover and climatic information for urban, suburban and rural-areas.

<table>
<thead>
<tr>
<th>District</th>
<th>Rural</th>
<th>Suburban</th>
<th>Urban</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Tai Mo Shan</td>
<td>Lam Tsuen</td>
<td>Shatin</td>
</tr>
<tr>
<td>Optimum scale (m²)</td>
<td>700</td>
<td>700</td>
<td>450</td>
</tr>
<tr>
<td>Green area (%)</td>
<td>80</td>
<td>86.4</td>
<td>38</td>
</tr>
<tr>
<td>Wind speed (ms⁻¹)</td>
<td>8.3⁺</td>
<td>n/a</td>
<td>0.3</td>
</tr>
<tr>
<td>Average $T_a$ (°C)⁺⁺⁺</td>
<td>13.8</td>
<td>10.7</td>
<td>14.4</td>
</tr>
<tr>
<td>Max and min $T_a$ (°C)⁺⁺⁺</td>
<td>14.6/13.3</td>
<td>14.6/10.4</td>
<td>15/13.9</td>
</tr>
<tr>
<td>Average $T_s$ (°C)⁺⁺⁺</td>
<td>14.2</td>
<td>13.2</td>
<td>16.8</td>
</tr>
</tbody>
</table>

⁺Top of mountain.
⁺⁺⁺From mobile measurements.
⁺⁺⁺From 10 m $T_s$ image.
It is thought that the much lower variability of the correlation for urban areas than for suburban and rural may be due to the development of a strong urban boundary layer over Kowloon. This is indicated by much higher air temperatures for Kowloon than for the smaller towns of Shatin and Yuen Long in the New Territories, i.e. the lowest temperature for Kowloon is higher than the highest temperatures in these new towns (table 1). Kowloon’s urban boundary layer capped by an inversion would reinforce urban heat island development with downward heat flux to the urban atmosphere, thereby creating more uniform thermal conditions within the underlying urban canopy layer. Variable wind speeds (higher in those suburban and rural areas above inversion height of c.600 m, and lower speeds in urban areas which are all below this) would also explain the higher variability of the correlations for suburban and rural areas. For example, at the top of Tai Mo Shan mountain 8 ms\(^{-1}\) was recorded at the image time.

The wide range of scales for air–surface temperature correlations noted by previous studies, e.g. 200–800 m by Kawashima et al. (2000) for combined land cover types over a whole Landsat image, and the 100–1000 m of Schmid et al. (1991) for homogeneous suburban areas, encompass those observed in the present study for the three land cover types individually. However, when air temperatures are derived from regression equations for individual land cover types at their optimum resolution, image-derived air temperatures are much closer to the field data than when air temperature is derived from regression of the whole image, i.e. all land cover types combined (table 1).

The derivation of the results from a night-time image with stable atmosphere, low boundary layer and resulting strong influence of local surface structure on air temperatures may increase the spatial variability in \(T_a\) and it is possible that scale lengths would be greater during the day and/or with higher lapse rates. Indeed Kawashima et al. (2000) noted larger horizontal scales of night-time air temperature cooling on image dates with higher lapse rates.

7. Conclusion

This is the first study to examine the relationship between air temperature and satellite-derived surface temperature for specific land cover types, and the first study to employ extensive \textit{in situ} air temperature data: in this case a mobile air temperature traverse of c.130 km length. The observed optimum scale lengths for the correspondence between air and surface temperature of 200 m, 450 m and 700 m for urban, suburban and rural land cover types respectively, fall within the much wider range of lengths (of 100–1000 m) observed by previous studies for general land cover types. The observed scale lengths indicate suitable spatial resolutions for these cover types for air temperature estimation from satellite-derived surface temperatures. Thus for urban heat island analysis a spatial resolution of 200 m, which approximates the scale of urban morphology, may give the best representation of air temperature within the urban canopy layer, and higher resolutions such as the 90 m of ASTER or 60 m of Landsat ETM+ may misrepresent air temperature by suggesting greater spatial variability than is actually present. On the other hand, air temperature variations in the order of several hundreds of metres as suggested by previous studies based on data collected for general land cover types, would omit the detail needed for urban heat island analysis. The results do not imply that thermal sensor resolutions higher than 200 m are not useful, since the emissivity correction procedure which is necessary to obtain accurate \(T_s\) values is specific to surface
material types, and requires a level of detail comparable to heterogeneous urban surfaces (Nichol in press). While the study is based on a single image obtained on a winter night, with a well developed urban heat island, the observations fall within those of previous daytime studies, and in urban areas correspond to the general scale of the building and street pattern.

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