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High-resolution Urban Thermal Sharpener (HUTS)

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Abstract

A high resolution urban thermal sharpener (HUTS) was developed that increases the resolution of thermal infrared (TIR) data to that of visible and near infrared (VNIR) data by fitting the relationship between radiometric surface temperature, normalized difference vegetation index (NDVI) and surface albedo (α). HUTS was applied to TIR data aggregated to 90 m to represent a satellite acquired dataset and validated against the measured 10 m data from aircraft over San Juan, Puerto Rico. HUTS sharpening reduced the root mean square error of surface temperature at the high resolution by 17 % compared to no sharpening and outperformed other sharpening methods. HUTS is proposed as a useful tool to study urban meteorology and climatology at the microscale using ASTER satellite data.

Keywords

Land surface temperature, Thermal sharpening, Urban heat island, Urban meteorology

20 1. Introduction

21 Satellites acquire thermal infrared (TIR) data to compute land surface temperature (LST) at a
22 resolution as high as 60 m (Landsat ETM+). This information can be used to study the impact of
23 urbanization such as the Surface Urban Heat Island (SUHI) which describes the increase in
24 (radiometric) LST in an urban area compared to surrounding rural areas (Voogt and Oke, 2003).
25 UHIs have fundamental impacts on meteorology (e.g. land-sea breezes, Lebassi et al. 2009), air
26 quality, public health (e.g. heat related deaths, Beniston, 2004), energy consumption, and
27 economics. The global coverage of satellites allowed quantifying and studying the SUHI in e.g.
28 Houston, Texas (Streutker 2003), Indianapolis, Indiana (Wilson et al. 2003), and 18 Asian mega
29 cities (Hung et al. 2006). While satellite TIR resolution resolves the scales of urban-rural LST
30 differences, it is not sufficient to resolve most urban features (roads, buildings) to study
31 microclimates and human comfort in urban areas.

32 As the pace of urbanization increases, studies on the microclimate within urban areas
33 are becoming more important as urban canyon LST affects pedestrian heat stress (Crutzen
34 2004) and building energy use (Yaghoobian et al. 2010). High resolution TIR data from remote
35 sensors flown on aircraft (e.g. NASA's Advanced Thermal and Land Applications Sensor, ATLAS,
36 5 m to 10 m resolution, depending on flight altitude) has been used to study the surface
37 microclimate over Huntsville, Alabama (Lo et al. 1997), and generate thermal, land cover
38 classification, and urban fabric maps for Atlanta, Georgia, Baton Rouge, Louisiana, Salt Lake City,
39 Utah, and Sacramento, California (Quattrochi et al. 2000). A one-day intensive experiment was
40 conducted in Phoenix, Arizona using airborne IR thermography to investigate the UHI at

41 different spatial scales (Di Sabatino et al. 2009). Airborne remote sensing campaigns are limited
42 in spatial extent and repeat cycle due to high cost. As each urban microclimate is unique due to
43 urban fabric and meteorology, a tool that would allow the downscaling of global satellite
44 datasets in urban areas would be extremely useful. The utility of global and repeating high
45 resolution TIR data motivates thermal sharpening, or estimating the TIR data at higher
46 resolution using complementary information available at that resolution.

47 Visible and Near Infrared (VNIR) data can generally be acquired at higher resolution than TIR
48 as a consequence of their shorter wavelength. Kustas et al. (2003) leveraged higher resolution
49 VNIR data by relating LST to the normalized difference vegetative index (NDVI) at the lower
50 resolution (96 m) and then applying the relation at the higher resolution available for NDVI (24
51 m). Agam et al. (2007) replaced NDVI by a simplified fractional vegetation cover and named the
52 method TsHARP. TsHARP provided reasonably accurate high resolution (60 m) TIR maps from 1
53 km TIR data, but the accuracy decreased with increased resolution of the sharpened map
54 (Agam et al., 2008). In urban areas, solar reflectance (albedo) is another determinant of LST.
55 While LST is a function of land class(e.g. deep water and shadowed areas are cooler than
56 equally low-albedo sunlit surfaces) , Small (2006) found that within unshaded land classes
57 albedo correlates well with LST.

58 Guo and Moore (1998) sharpened LST using the VNIR bands to identify topographic
59 variations. While LST for areas with varied topography and homogeneous land cover where sun
60 angle is the driving force for LST differences can be predicted accurately, this method is not
61 applicable to flat urban areas with very heterogeneous land covers. Nichol (2009) sharpened a

62 nighttime ASTER image of Hong Kong using emissivities based on land class from the MODIS
63 emissivity library. However, emissivity is not the main determinant of LST during the daytime,
64 and the accuracy of the land class based emissivities is questionable when emissivity libraries
65 are used.

66 In this study high resolution ATLAS data (Section 2) over urban Puerto Rico is analyzed. Based
67 on the relationship between TIR derived LSTs and VNIR signals (Section 3), a High-resolution
68 Urban Thermal Sharpening method (HUTS) is proposed using *NDVI* and albedo from the VNIR
69 channels (Section 4). The high resolution ATLAS data are used to quantify the accuracy of HUTS
70 and TsHARP (Section 5).

71 **2. ATLAS Airborne Data**

72 NASA ATLAS data taken over the greater San Juan, Puerto Rico area on February 16, 2004
73 (Gonzalez et al. 2005, 2006) at 10 m resolution over 15 spectral channels (Table 1) is used. The
74 study focuses on a 900 x 720 pixel (9 km x 7.2 km) urban and suburban, cloud-free region from
75 the 3rd flight line at 5200 m altitude, taken between 1507 and 1512 local standard time (AST,
76 Fig. 1). Air temperature on this day averaged 26 °C with a high of 28.5 °C and a low of 23 °C,
77 Humidity was an average of 80%, varying from 59% to 100%. Winds were from the East at an
78 average 4.5 m s⁻¹, but were sustained at 7.6 -9.4 m s⁻¹ during 1407-1612 AST (NWS Daily
79 Summary). Since the study area is flat, topographic shading is minimal. Shadows will be present
80 due to (primarily low) buildings and the early afternoon flight time. Considering solar geometry
81 at the time of the flight, the shadow length for a 3 m tall building would be 2.00 m for a North –
82 South wall and 2.66 m for an East – West wall. Since shaded areas have small surface

83 temperature (T_s) and appear to have a low reflectance, the expected relationship between
84 reflectance and T_s is not preserved at shaded surfaces.

85 ATLAS calibration and correction is described by Rickman et al. (2000). From the spectral
86 irradiance in each band [$\text{W cm}^{-2} \text{sr}^{-1} \mu^{-1}$] the following quantities were computed. *NDVI* was
87 calculated as in previous ATLAS studies (e.g. Lo et al., 1997) as:

$$88 \quad NDVI = \frac{(b_6 - b_3)}{(b_6 + b_3)}. \quad (1)$$

89 Surface albedo was calculated as the ratio of incident irradiance that is reflected in the VNIR
90 (bands 1-6). T_s was computed assuming an emissivity of 0.98. Since emissivities in an urban
91 landscape varies from 0.91 to 0.99 (MODIS emissivity library), the surface temperatures used
92 throughout this study should be considered as thermal energy expressed in temperature units.
93 A calculation based on actual emissivity would increase T_s . Emissivity could be obtained at high
94 resolution based on land cover class (Nichol 2009) or at low resolution through methods that
95 utilize multiple TIR bands, e.g. the Grey Body Emissivity (Barducci and Pippi 1996) or
96 Temperature Emissivity Separation methods (Kealy and Hook 1993). These calculations are left
97 to future work.

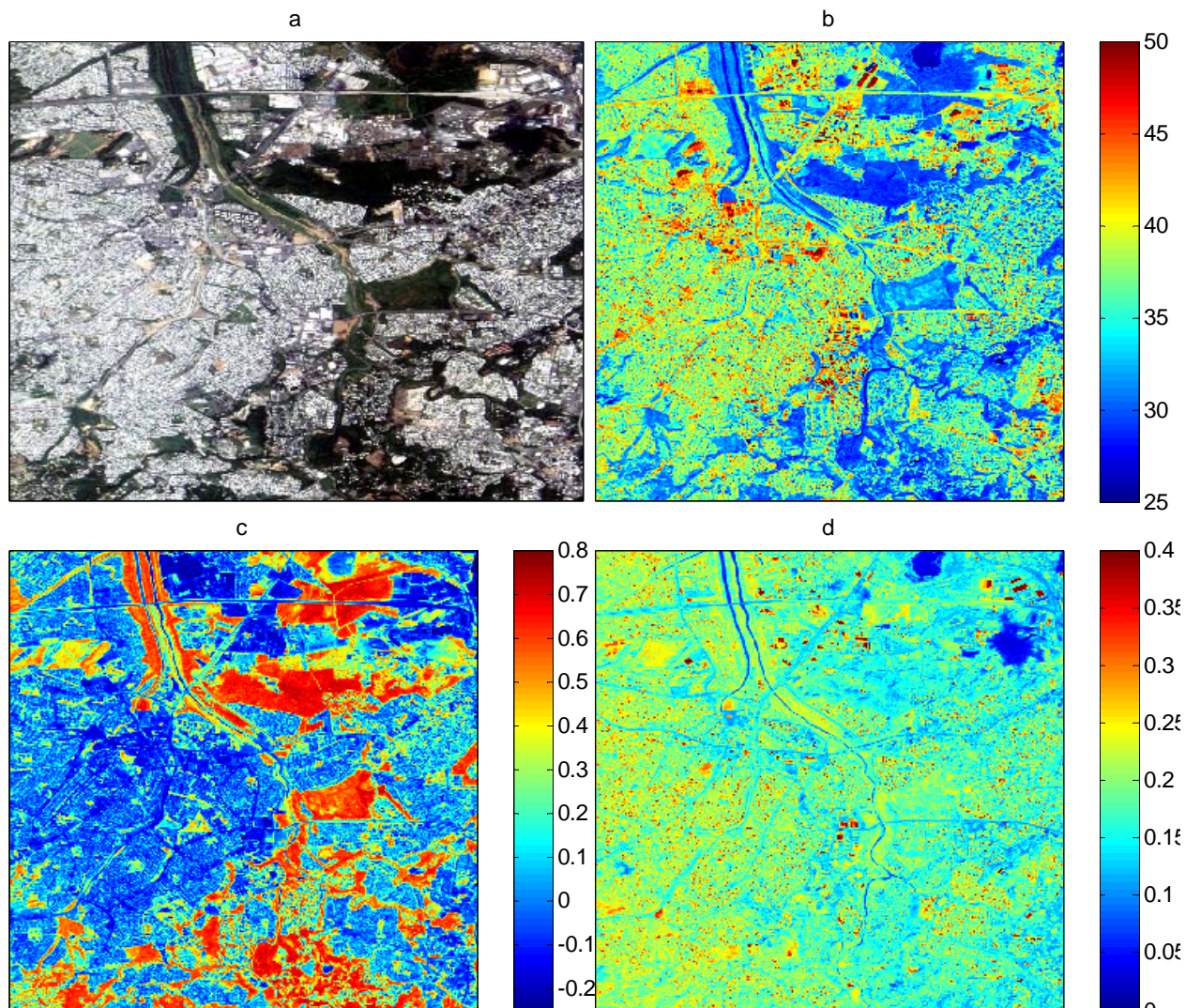
98 ATLAS data were aggregated to 90 m resolution and to simulate ASTER satellite data. The
99 original 10 m resolution data is used as the 'measured temperature' to evaluate the accuracy of
100 the sharpening methods similarly as in Agam et al. (2008). *NDVI* and T_s were aggregated by
101 averaging *NDVI* and TIR irradiance from the 10 m high resolution pixels, respectively.

102

103 **Table 1: ATLAS bands and approximate band widths. Bands 3 and 6 are used for the NDVI calculation. Band 12 is**
104 **used to calculate T_s .**

| ATLAS band | Approximate Bandwidth (μm) |
|------------|-----------------------------------------|
| 1 | 0.45 – 0.52 |
| 2 | 0.52 – 0.60 |
| 3 | 0.60 – 0.63 |
| 4 | 0.63 – 0.69 |
| 5 | 0.69 – 0.76 |
| 6 | 0.76 – 0.90 |
| 7 | 1.55 – 1.75 |
| 8 | 2.08 – 2.35 |
| 9 | 3.35 – 4.20 |
| 10 | 8.20 – 8.60 |
| 11 | 8.60 – 9.00 |
| 12 | 9.00 – 9.40 |
| 13 | 9.60 – 10.2 |
| 14 | 10.2 – 11.2 |
| 15 | 11.2 – 12.2 |

105



106

107 **Figure 1: 9 x 7.2 km images of corrected and calibrated ATLAS measurements over a region of San Juan, Puerto**
 108 **Rico centered at 18.3933°N, 66.1447°W on February 16, 2004 from 1507-1512 AST. (a) visible composite image;**
 109 **(b) Surface Temperature; (c) NDVI; (d) albedo. The high albedo features in the northern region are commercial**
 110 **buildings. The large, white region in the West (Fig. 1a) is suburban residential. The high NDVI regions are densely**
 111 **vegetated. Rio Hondo river runs North-South from the top of the image.**

112

113 3. Relationship between VNIR and TIR data

114 3.1 High resolution (10 m)

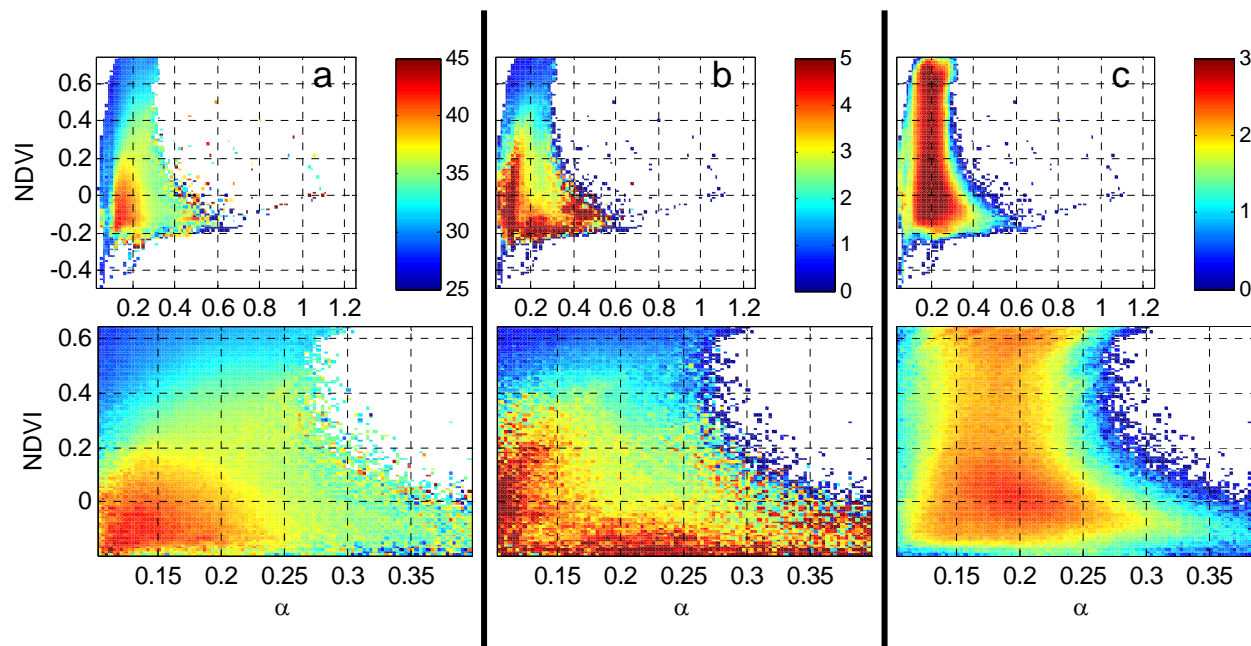
115 The assumption behind any thermal sharpening tool is that a relationship must exist between

116 the TIR data and the visible and near-infrared (VNIR) data at the high resolution. Since all ATLAS

117 bands were acquired at 10 m resolution, this assumption could be tested by investigating the
118 relationship between $NDVI$, α , and T_s (Fig. 2). Each 10 m pixel was sorted into one of 100 $NDVI$ x
119 100 α bins, and the average T_s of each bin, along with the standard deviation and total number
120 of pixels in the bin is displayed in Figure 2. This display format also allows visualization of the
121 relationship of T_s to $NDVI$ at any constant α or T_s to α at any constant $NDVI$. For example,
122 consider the vertical dashed line in Fig. 2a at $\alpha = 0.2$. Going from $NDVI$ of 0.0 to 0.6, T_s
123 decreases from about 40 to 30 °C. Fig. 2b shows the variance of the pixels along that same line
124 to be less than 3 °C (i.e. much less than the observed change in average T_s), while Fig. 2c shows
125 that the line is in a high density of samples, with over 100 samples contributing to each mean T_s
126 and standard deviation pixel. Consequently, T_s decreases with $NDVI$, but the slope is different
127 for different α .

128 Figure 2 shows that, as expected, the highest T_s occur for $-0.2 < NDVI < 0.0$ and $0.1 < \alpha < 0.25$,
129 which are typical properties of unvegetated, man-made urban materials. With increasing $NDVI$,
130 T_s decreases as more vegetation leads to more latent heat flux and evaporative cooling. $NDVI <$
131 -0.25 shows water bodies with low albedo and negative $NDVI$. Figure 2 also shows a strong
132 dependence of T_s on α , which differs by $NDVI$. In the built up region ($-0.2 < NDVI < 0.2$) an
133 increase in α leads to a decrease in T_s , as lighter surfaces reflect more solar radiation. Increasing
134 α in the vegetative region ($NDVI > 0.2$) leads to an increase in T_s since darker vegetative areas
135 tend to have denser and healthier (more transpiring) vegetation than drier, stressed vegetation.
136 Overall, for the region with the greatest density of samples, a bivariate function $T_s(NDVI, \alpha)$ is
137 required to fit the data with little scatter (small standard deviation of T_s in Fig. 2b). Since the

138 relationship between T_s , $NDVI$ and α is nonlinear, higher order polynomials are required to
 139 describe it.



140
 141

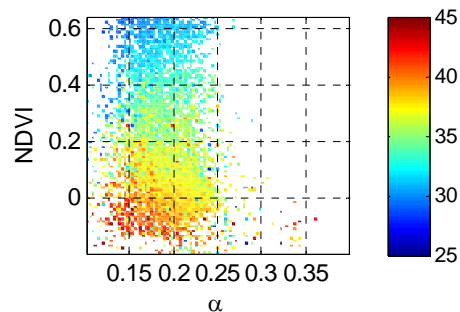
142 **Figure 2: (a) Mean and (b) standard deviation of T_s [$^{\circ}\text{C}$] and (c) histogram [$\log_{10}(\# \text{ of pixels})$] vs. $NDVI$ and albedo**
 143 **for (top) all data and (bottom) region with the majority of the data.**

144 The relationships shown in Fig. 2 also reveal outliers with unrealistic values of $\alpha > 0.8$ and
 145 seemingly erroneous cases of high T_s and high albedo over rooftops. These albedo outliers may
 146 be due to roof coverings such as gravel that have non-lambertian reflectance characteristics.

147 3.2 Low resolution (90 m)

148 A strong relationship between T_s vs. $NDVI$ and α exists at the 10 m resolution (Fig. 2). When
 149 applying sharpening techniques to satellite data, however, only low resolution T_s will be
 150 available for training this relationship. To test the assumption of scale-invariance, the
 151 relationship of T_s vs. $NDVI$ and α were again compared at the low resolution (Figure 3). Though
 152 the low resolution data cover a smaller $NDVI$ and α range than the high resolution data, the

153 NDVI relationship is consistent. The analysis in Section 3 motivates the development of the
 154 sharpening method, which consists of fitting a 4th order, bivariate $T_s(NDVI, \alpha)$ polynomial to the
 155 low resolution training data (Section 4.3). The aim of the model is to fit Fig. 3 to recreate the
 156 true relationship observed in Fig. 2a and use it to assign high resolution T_s . Assuming this can be
 157 done accurately, random errors in the sharpened temperatures will be due primarily to
 158 deviations shown in Fig. 2c.



159
 160 **Figure 3: $NDVI$ and $albedo$ vs. T_s [$^{\circ}C$] at the aggregated resolution of 90 m. Due to the low number of pixels, the**
 161 **majority of the bins contain less than 5 pixels, making histogram and standard deviation figures (as used in Fig.**
 162 **2) irrelevant.**

163

164 4. Sharpening Methodology

165 4.1 UniTrad

166 UniTrad is the base case, where the high resolution T_s is assumed to be uniform within the
 167 underlying low resolution pixel (Kustas, 2003).

168 4.2 TsHARP

169 The TsHARP method (Agam et al. 2007) is applied by calculating a simplified fractional
 170 vegetation cover ($f_{cs90} = (1 - NDVI_{90})^{0.625}$) at the low 90 m resolution. A linear regression
 171 between f_{cs90} and T_s at the low resolution yields the coefficients c_0 and c_1 in equation (2):

$$172 \quad T_{s90} = c_0 + c_1 f_{cs90}. \quad (2)$$

173 Each high resolution pixel is then assigned a temperature based on the high resolution *NDVI*:

$$174 \quad T_s = c_0 + c_1 (1 - NDVI)^{0.625} + dT_s \quad (3)$$

175 and a difference $dT_s = T_{s90} - \hat{T}_{s90}$ which corrects for the difference in T_s between measured
 176 T_{s90} and \hat{T}_{s90} , the mean value of the sharpened surface temperature within each low
 177 resolution pixel. The addition of dT_s conserves energy within each low resolution pixel such
 178 that aggregating the sharpened T_s reproduces the original low resolution T_{s90} .

179 *4.3 High resolution Urban Thermal Sharpener (HUTS)*

180 Four steps were defined that outline the approach to sharpening which are similar to the
 181 procedure in TsHARP. Each step was individually optimized in the development of HUTS.

182 *Aggregation* consists of averaging *NDVI* and α over each low resolution pixel.

183 *Training* is conducted by applying multi-variate regression to solve for the vector \mathbf{P} ($\mathbf{P} = [p_1 \ p_2 \ \dots$
 184 $p_{15}]$) of coefficients for the 4th order, bivariate regression of T_{s90} based on the 90 m resolution
 185 *NDVI* and α .

186 *Sharpening* is conducted by applying Eq. 4 to the *NDVI* and α of each high resolution pixel to
 187 obtain the high resolution T_s :

$$\begin{aligned}
188 \quad T_s &= p_1 NDVI^4 + p_2 NDVI^3 \alpha + p_3 NDVI^2 \alpha^2 + p_4 NDVI \alpha^3 + p_5 \alpha^4 + p_6 NDVI^3 + p_7 NDVI^2 \alpha + \\
189 \quad &p_8 NDVI \alpha^2 + p_9 \alpha^3 + p_{10} NDVI^2 + p_{11} NDVI \alpha + p_{12} \alpha^2 + p_{13} NDVI + p_{14} \alpha + p_{15} \quad (4)
\end{aligned}$$

190 *Quality control* is then performed, as the regression is poorly fit outside of the region with a
191 high density of data points. A reasonable temperature is defined as $27^\circ\text{C} < T_s < 60^\circ\text{C}$, where
192 the lower limit is set by the water surface temperature and the upper limit is 5°C larger than
193 the highest value of T_{s90} . If the temperature is outside the acceptable range, it is defined
194 through an interpolation of the surrounding 5x5 pixel block weighted by distance. In the case
195 that the surrounding 5x5 pixel block does not contain a pixel with an acceptable T_s , an iterative
196 process is used until all pixels have been assigned a T_s . Finally, the sharpened pixel
197 temperatures are corrected by applying the same energy balance procedure used for TsHARP.
198 [An uncertainty weighted correction was also attempted, where the uncertainty metric was
199 assigned to each pixel based on the variability of T_s within its range of $NDVI$ and α and whether
200 or not it was acquired through interpolation. The uncertainty was then used as a weighting
201 factor where the pixels with the greatest uncertainty were changed the most to achieve energy
202 balance. However, this method resulted in larger sharpening errors and was discarded.]

203

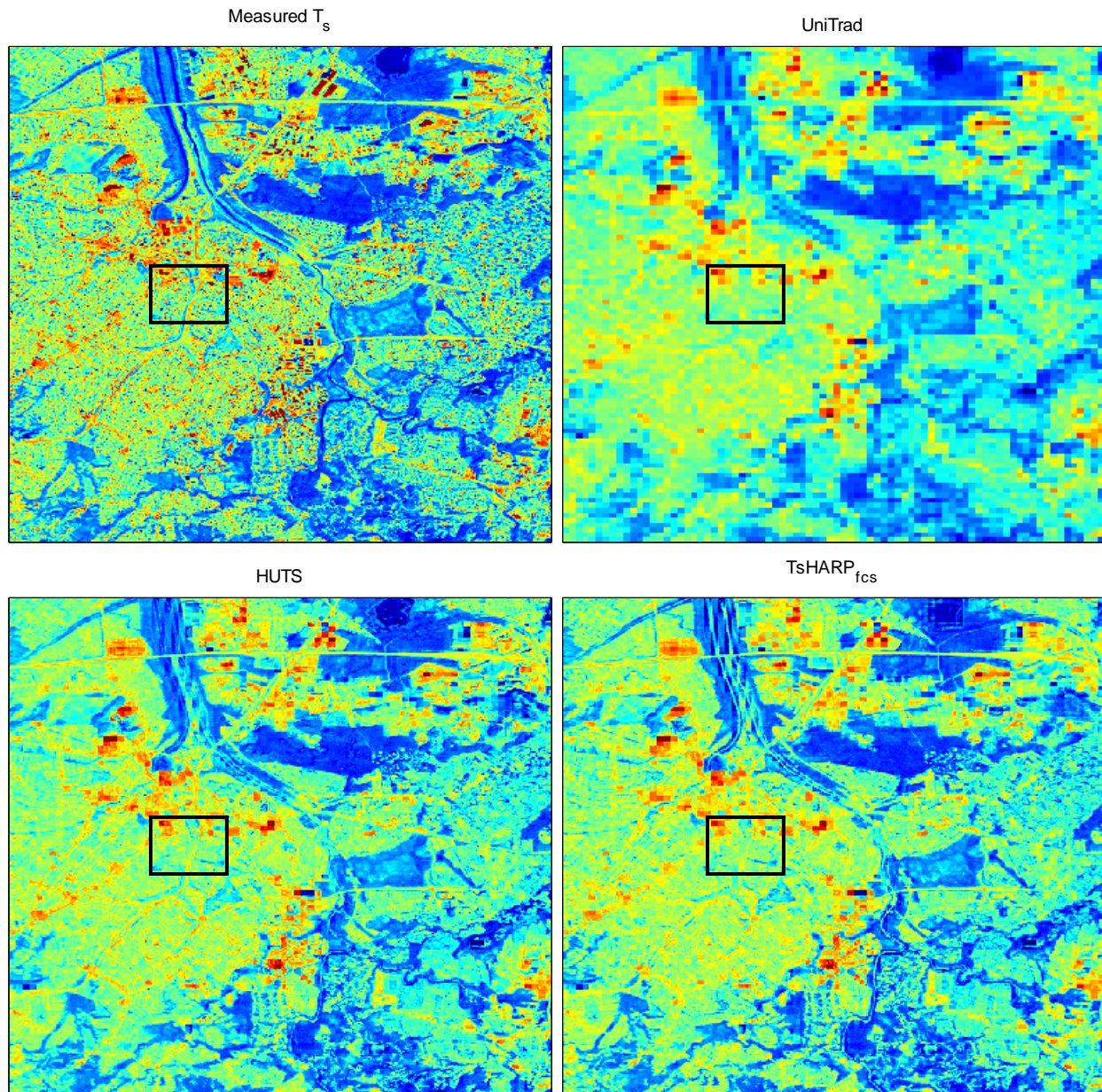
204 5. Results

205 5.1 Sharpened images and qualitative analysis

206 Figure 4 shows the measured 10 m T_s , the unsharpened 90 m image, and the sharpened
207 image from both HUTS and TsHARP. Water pixels (from the rivers) can be ignored as they were

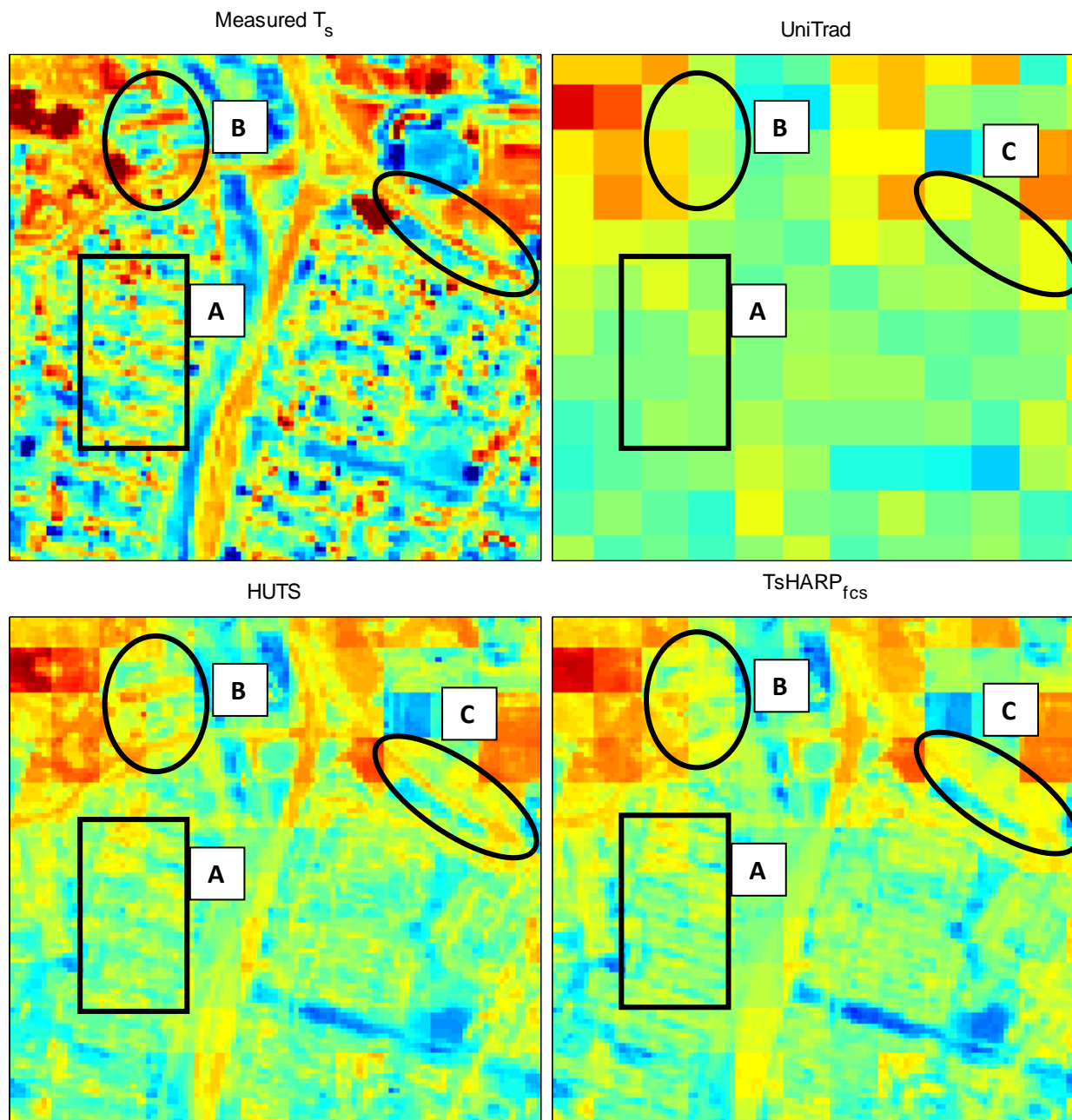
208 not taken into consideration when training the sharpening method, though the error in their
209 estimation contributes to the error metrics in section 5.3. The improvement of both TsHARP
210 and HUTS over UniTrad is evident in Fig. 4. Major landscape features such as parks are clearly
211 delineated in TsHARP and HUTS. Small urban features such as roads which are barely visible in
212 UniTrad become well resolved in TSHARP and HUTS. However, smaller urban features which
213 cause variability at the high resolution (e.g. in and around the black box) are not depicted
214 accurately. Consequently, the quality of sharpening of smaller urban features requires further
215 investigation.

216 Figure 5 shows the same results zoomed into a mixed urban and suburban region. In the
217 suburban areas (region A) HUTS accurately resolves the T_s patterns over roads, yards, and
218 buildings, but not as distinctly as the measured T_s . TsHARP, however, inaccurately shows roads
219 to be cooler than buildings since they have a higher NDVI. There are some regions where HUTS
220 is visibly superior to TsHARP, but both do not resolve or represent microscale variability. Region
221 B highlights a parking lot, where HUTS captures the variability between the lot and surrounding
222 buildings that TsHARP does not. Region C highlights a boundary between an asphalt road and
223 dirt to the North which is resolved by HUTS but not in TsHARP. Both TsHARP and HUTS do not
224 represent the true variability of T_s which is a result of the averaging through the regression
225 polynomial. There sometimes occur large gradients in T_s along the boundaries of the coarse
226 pixels (e.g. north-west part of Fig. 5), which is a result of forcing energy conservation across the
227 low resolution pixels. The very cold (very warm) 'outlier' high resolution pixels are
228 overpredicted (underpredicted) by the sharpening polynomial leading to a erroneous decrease
229 (increase) in temperature for all high resolution pixels once energy conservation is applied.



230

231 **Figure 4:** T_s maps of the area shown in Fig. 1 including measured surface temperature at 10 m, unsharpened
 232 surface temperature at 90 m (UniTrad), and sharpened temperature for both HUTS and TsHARP. The 900 x 720
 233 pixel image covers a region of 9.0 x 7.2 km. Black boxes outline the close-up region shown in Fig. 5.



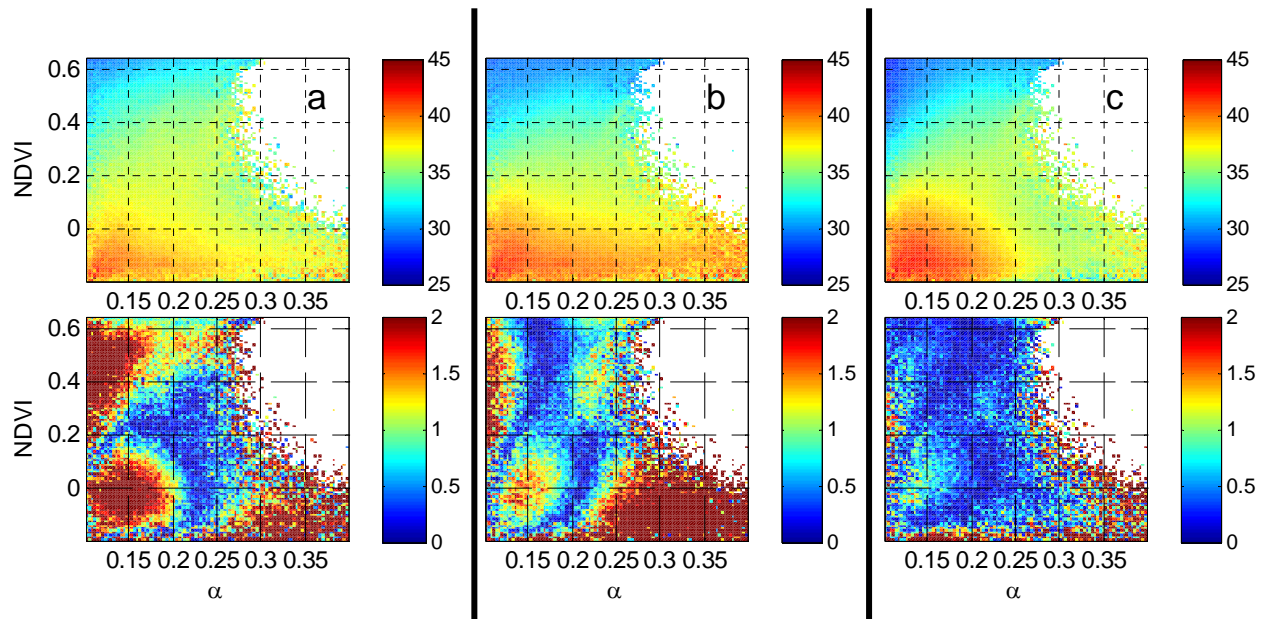
234

235 **Figure 5: Sharpened T_s zoomed in to a 100 x 100 pixel urban region (centered at 18.390698°N, 66.153084°W) at**
 236 **10 m resolution. The figure shows a major highway intersection (CII 2 and Carr 174). To the south of the east-**
 237 **west highway are mostly residential neighborhoods with trees, while parks, parking lots, and commercial**
 238 **buildings are to the north. West of the north-south highway is a waterway.**

239

240 *5.2 Distribution of sharpened T_s vs. NDVI and α*

241 The distribution of sharpened T_s stratified by $NDVI$ and α is shown in Fig. 6 to determine how
 242 the relationships are represented after sharpening. Despite the limitations of the low resolution
 243 training set, HUTS recreates the high resolution relationship more accurately than TsHARP.
 244 Most of the differences are in regions of high T_s variability. There, the 4th order polynomial
 245 cannot resolve the differences in T_s or application of energy conservation over the low
 246 resolution pixel may result in erroneous corrections. Presumably other (unobserved) variables
 247 such as geometrical or physical properties of the urban fabric would have to be considered to
 248 explain the T_s variability. However, HUTS shows a decreases in error compared to TsHARP
 249 especially for the higher albedo for both vegetated ($NDVI \sim 0.4$) and urban pixels ($NDVI \sim 0$).



250

251 **Figure 6: T_s vs $NDVI$ and α for UniTrad (a), TsHARP (b), and HUTS (a) (top) and difference to measured T_s**
 252 **(bottom) in $^{\circ}C$.**

253

254 5.3 Error and correlation metrics and accuracy by land class

255 Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and correlation coefficient (R)
 256 were used to quantify the difference between sharpened and measured T_s at high resolution
 257 for the entire 900 x 720 pixel image (Table 2). Over the entire image, HUTS improves upon
 258 TsHARP about as much as TsHARP improves upon UniTrad for both error measures. Comparing
 259 HUTS directly to UniTrad shows a 17% reduction in RMSE and 22% reduction in MAE.

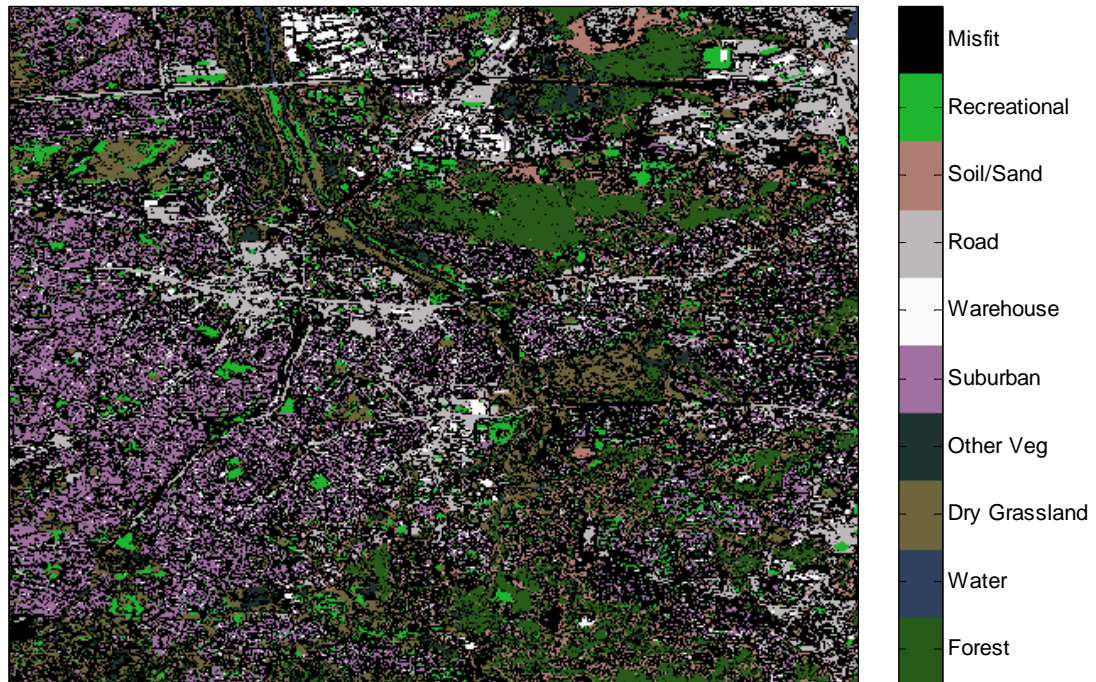
260 **Table 2: Error in the estimation of sharpened T_s over the image in Fig. 4.**

| Method | RMSE [K] | MAE [K] | R | MBE [K] |
|-----------------------|----------|---------|-------|---------|
| UniTrad | 3.33 | 2.48 | 0.712 | 0.000 |
| TsHARP _{fcs} | 3.07 | 2.17 | 0.765 | -0.019 |
| HUTS | 2.76 | 1.94 | 0.813 | -0.015 |

261

262 Since HUTS is developed specifically for use in urban areas it is useful to examine its accuracy
 263 within various land classes. For classification a training set was developed based on manual
 264 selection of pixels and the classification function in MATLAB's image processing toolbox was
 265 used on high resolution ATLAS bands 1, 2, 3, 5, 7, 8, as well as $NDVI$ and α (Fig. 7).

266 The land classes used were motivated by Nichol (2009) and included 'Forest', 'Water', 'Dry
 267 Grassland', 'Other Vegetation', 'Urban', and 'Soil/Sand'. However, 'Urban' was replaced by
 268 'Suburban', 'Warehouse', 'Road', and 'Recreation'. The classification also contains a 'misfit'
 269 class with pixels that were not highly matched with any class ('highly matched' = >80%
 270 agreement with algorithm-defined parameters for any class).



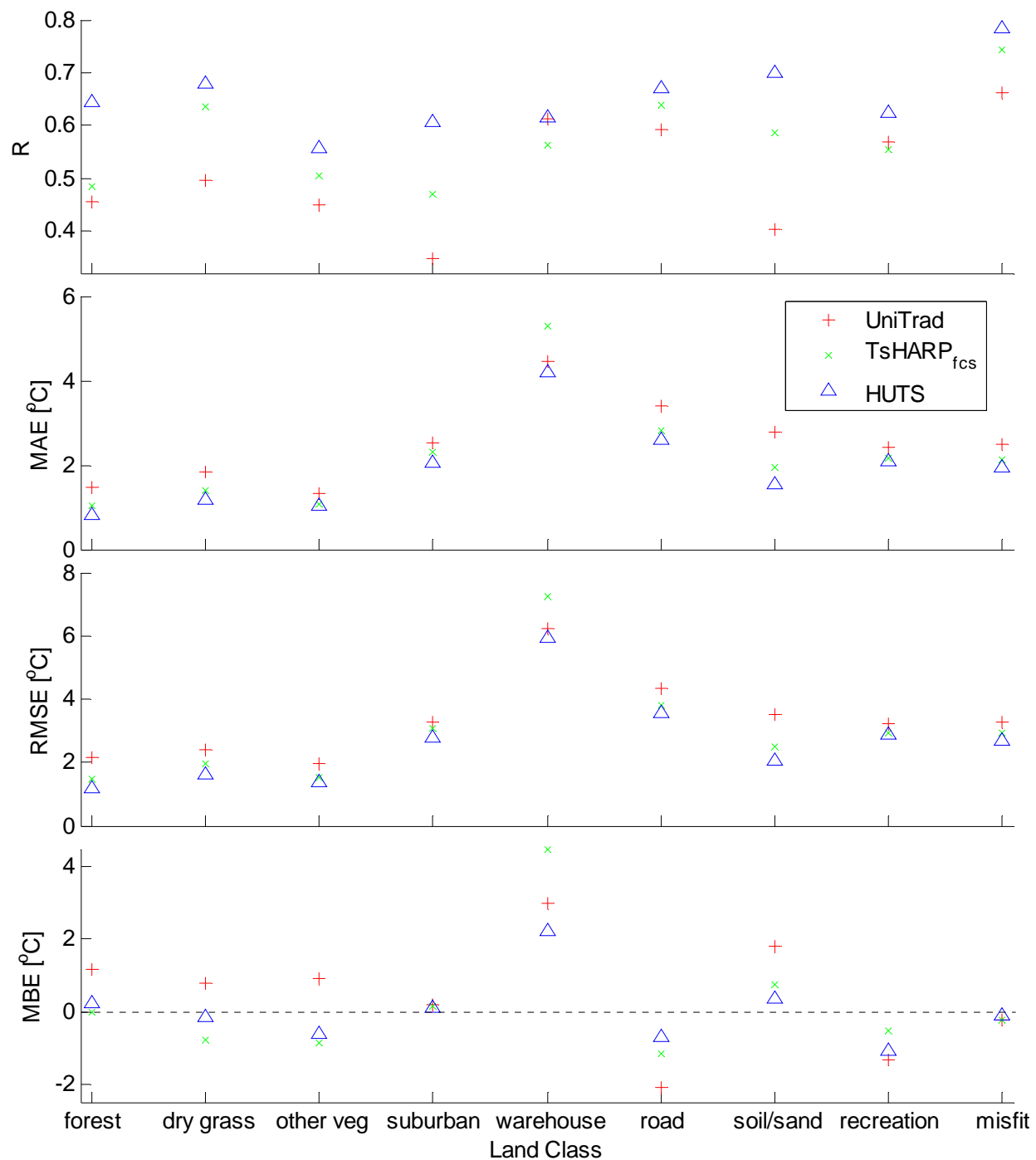
271

272 **Figure 7: Scene (same as Fig. 4) with land cover classification into 9 classes. The class ‘misfit’ contains pixels with**
 273 **less than 80% fit to any category.**

274 RMSE, MAE, mean bias error (MBE) and correlation coefficient were calculated within each land
 275 cover class (Figure 8). Since ‘Other Vegetation’ has a much lower number of pixels than the
 276 other classes, the result may not be significant. The high errors in ‘warehouse’ class are partially
 277 due to the high albedo ‘outliers’ observed in Fig. 2 which account for many pixels in the
 278 ‘warehouse’ class.

279 The ‘suburban’ class is poorly defined since at 10 m resolution it is a combination of landcover
 280 types. Instead of using the image processing toolbox to determine suburban pixels, the ‘road’,
 281 ‘water’, and ‘recreational’ pixels were excluded from a residential area of 200 x 200 pixels to
 282 form the suburban class. While the MBE for all methods in the suburban class is nearly zero,
 283 HUTS has a significantly higher correlation, meaning that it better captures the variability in

284 suburban LST caused by houses, yards, and mixed pixels. For the other land classes, HUTS
 285 performs measurably better than both TsHARP and UniTrad, especially for classes defining
 286 small scale features such as 'road' and 'soil/sand'.



287

288 **Figure 8: Graphical representation of correlation coefficient, MAE, RMSE, and MBE in sharpened T_s by land class.**

289 6. Conclusions

290 Albedo and vegetation are expected to be important determinants of land surface
291 temperatures (LST) in urban areas. The **High-resolution Urban Thermal Sharpener (HUTS)**
292 method was motivated by analysis of the high resolution relationship between the TIR and VNIR
293 signal (NDVI and albedo) from 10 m resolution ATLAS data over Puerto Rico. It was
294 demonstrated that a low resolution (90 m) NDVI and albedo training set preserved the
295 observed relationship to LST at high resolution. The training relationship was applied to
296 estimate high resolution LST from 90 m LST sharpened using the VNIR signal at 10 m resolution
297 over a 900 x 720 pixel image. Since HUTS can express the complex non-linear relationship
298 between LST, albedo, and NDVI, it performed significantly better than both no sharpening
299 (UniTrad) and an approach solely based on NDVI (TsHARP) based on qualitative comparison and
300 RMSE, MAE, and correlation coefficient. Overall, HUTS showed an improvement of over 0.5 °C
301 and over 17% in MAE and RMSE from no sharpening, more than twice the improvement from
302 the TsHARP method. A land classification was applied to the image, and sharpening accuracy
303 was assessed in each land class. The low MBE of HUTS indicated that the average LST of various
304 land classes in the HUTS sharpened image is a more realistic input to models for urban
305 microclimate or building energy use.

306 Since HUTS is a redistribution of LST based on assumed relationships, the source of error is
307 twofold. The first is variance of high resolution LST at constant NDVI and albedo. This is
308 quantified for the study area in Fig. 2b, and is less than 3 °C for the majority of the study area.
309 The second source of error is from the ability to train the high resolution relationship from the

310 low resolution data. This is quantified for the study area in Fig. 6c, and is less than 0.75 °C for
311 the majority of the study area. The assumed relationships are accurate, and the reallocation
312 results in higher accuracy than other sharpening methods.

313 While HUTS was trained in the same *study area* that was used for validation, since the
314 validation data (high resolution LST) is not used in the training this serves as an independent
315 validation of HUTS. However, our study does not evaluate whether the relationship between Ts,
316 NDVI and albedo is applicable across measurements platforms. While only a small area is
317 presented in this manuscript, HUTS was applied to other regions of the dataset with similar
318 results. Any other high resolution urban dataset could also be used for validation, and similar
319 results are expected.

320 HUTS is proposed as a method for providing an estimate of the TIR signature at the same
321 resolution as VNIR satellite data. Since it is based on physical parameters as opposed to lower
322 level parameters (direct numerical (DN) value, radiance at sensor, etc), HUTS is applicable to
323 calibrated datasets acquired from many remote sensing platforms. For example, HUTS can be
324 applied to widely available ASTER images to estimate LST at the 15 m VNIR resolution from the
325 measured 90 m TIR resolution. HUTS may also be applicable to lower resolution data such as
326 that from MODIS, where it could increase thermal IR resolution from 1000 m to ~ 250m. While
327 the MODIS resolution is too coarse to be of interest for many urban microclimate applications,
328 TsHARP was found to be more accurate when sharpening to lower resolutions (Agam et al.,
329 2008). In heterogeneous urban areas HUTS sharpened LST will provide more accurate input
330 data for studies on how varied land classifications and land use (LCLU) affect the thermal

331 response of the urban fabric and the urban microclimate. The scale of heterogeneity in surface
332 roughness impacts turbulent parameters such as blending height (Bou-Zeid and Parlange,
333 2007). Similarly, micro-scale heterogeneity in surface heat flux will impact flow and mixing in
334 urban canyons (Castillo et al. 2009), and HUTS can provide measured high-resolution surface
335 heat fluxes to input into simulations.

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342 **Appendix A: Sensitivity of HUTS**

343 Since various options exist for the implementation of HUTS, a brief justification on the
344 implementation and sensitivity to different options is included here.

345 Using an entire flight path for training Eq. 4, covering mountains and natural vegetation as well
346 as the urban area, made the sharpened T_s biased low and increased the RMSE and MAE by 0.1-
347 0.2 °C. This could be a result of lower terrain or the urban surface heat island effect that heats
348 urban surfaces compared to surrounding terrain with the same NDVI and albedo. A higher error
349 associated with a larger training set indicates that there are competing land cover types of
350 different T_s in the same $NDVI$ and α ranges and that the relationships developed through this

351 study are not universal. Rather, the training should only be conducted for the urban area where
352 the sharpening will be applied.

353 The training data was also used to generate a look-up table based on Fig. 3 to find the
354 sharpened T_s and the regression (Eq. 4) was only used on empty bins. While this method had a
355 significantly shorter computational time, the error measures increased by 10-20%. In addition,
356 the order of the regression was varied from 3 – 6. The 4th order regression was the most
357 accurate, with RMSE and MAE within 0.05 °C for the other orders.

358 The ‘reasonable range’ of T_s was chosen with the river temperature as the lower limit (for many
359 other urban areas an ocean temperature could be a good choice) and 5 °C higher than the
360 maximum low resolution temperature as the upper limit. Varying these limits by 5 °C changed
361 RMSE and MAE by less than 0.1 °C. Overall, while many aspects of HUTS can be changed, it
362 proves to be robust over a reasonable range of parameters.

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