

Crowdsourcing urban air temperatures from smartphone battery temperatures

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[1] Accurate air temperature observations in urban areas are important for meteorology and energy demand planning. They are indispensable to study the urban heat island effect and the adverse effects of high temperatures on human health. However, the availability of temperature observations in cities is often limited. Here we show that relatively accurate air temperature information for the urban canopy layer can be obtained from an alternative, nowadays omnipresent source: smartphones. In this study, battery temperatures were collected by an Android application for smartphones. A straightforward heat transfer model is employed to estimate daily mean air temperatures from smartphone battery temperatures for eight major cities around the world. The results demonstrate the enormous potential of this crowdsourcing application for real-time temperature monitoring in densely populated areas. **Citation:** Overeem, A., J. C. R. Robinson, H. Leijnse, G. J. Steeneveld, B. K. P. Horn, and R. Uijlenhoet (2013), Crowdsourcing urban air temperatures from smartphone battery temperatures, *Geophys. Res. Lett.*, 40, 4081–4085, doi:10.1002/grl.50786.

1. Introduction

[2] High temperatures can negatively influence human health [Laaidi et al., 2006]. For instance, in the summer of 2003, a heat wave caused increased mortality rates in France [Filleul et al., 2006; Le Tertre et al., 2006]. This is especially important in cities, where most people live and air temperature extremes are raised by the urban heat island, particularly during the night [Oke, 1982; Johnson, 1985; Souch and Grimmond, 2006; Steeneveld et al., 2011; Stewart and Oke, 2012]. The percentage of urban dwellers worldwide is projected to increase from 49% in 2005 to 60%

in 2030 [United Nations, 2005]. Moreover, energy demand planning [Allegrini et al., 2012] will become more challenging, given the projected climate change and its variability. In order to assess the resource implications of policy interventions and to design and operate efficient urban infrastructures such as energy systems, greater spatial and temporal resolutions are required in the underlying resource demand data. Unfortunately, only limited information is available [Keirstead and Sivakumar, 2012]. Hence, there is an urgent need for accurate air temperature observations, specifically in urban areas.

[3] The possibility of crowdsourcing urban observations employing smartphones has been identified in a recent report of the *National Research Council of the National Academies* [2012]. To increase the availability of air temperature observations in urban areas, we call on the help of smartphone users to obtain access to a yet untapped network of temperature sensors that could potentially collect worldwide temperature data at low cost in an automated fashion. This can be more cost-efficient than the installation of new weather stations, which moreover require maintenance and are only representative for a limited area. Lithium ion batteries have temperature sensors to prevent damage caused by attempts to charge them when the battery is too hot. Its signal does not provide a direct air temperature measurement, because the smartphone is a significant heat source itself, and because it is typically carried close to another heat source: the body of the user. The urban canopy layer consists of the air contained between the urban roughness elements (mainly buildings) [Oke, 1976]. Here we show how daily averaged air temperatures for eight major cities (> 2 million inhabitants) can be derived from smartphone battery temperature readings obtained from an Android application employing a straightforward heat transfer model (Figure 1 (left)). This is a first step toward trying to obtain even more relevant temperature information that would be useful for a variety of urban applications, e.g., an accurate estimate of urban canopy layer temperatures for the complex and diverse local and microscale environments in a city.

[4] Since 20% of the Earth's land surface has cellular telephone coverage [GSM Association, 2007] and 500 million devices [CNET, 2012] use the Android operating system, a huge potential exists for obtaining real-time air temperature maps from smartphones, especially in densely populated areas. For example, from 25 April 2012 to 22 April 2013, already over 530 thousand devices have contributed a total of over 220 million readings of battery temperatures across more than 200 countries/territories employing the Android application OpenSignal for smartphones (opensignal.com; recently also available for iOS), which crowdsources data relevant to wireless connectivity (Figure 1 (right)).

Additional supporting information can be found in the online version of this article.

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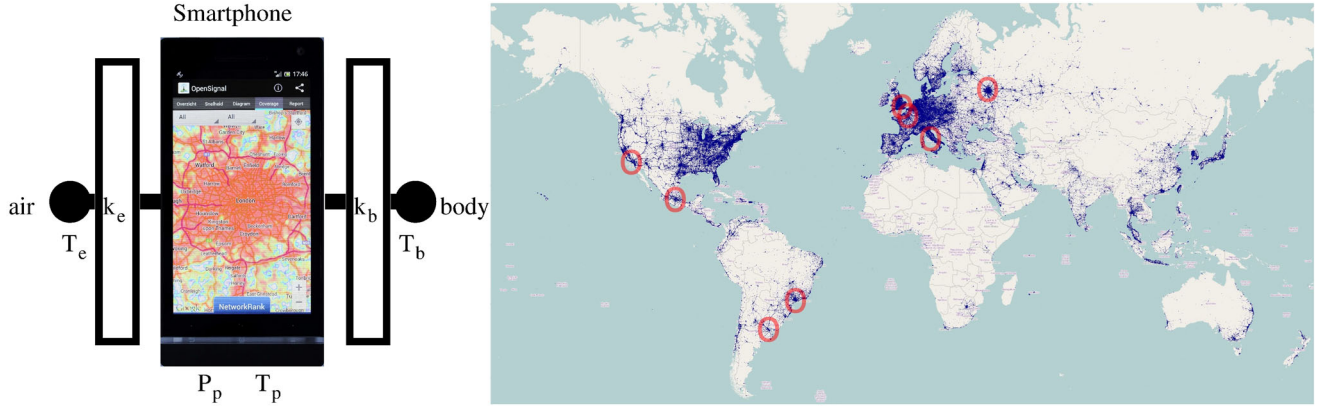


Figure 1. Heat transfer model and world map of battery temperature readings. (left) Smartphone’s battery temperature (T_p) can be retrieved using an Android application. Battery temperature is influenced by environmental temperature (T_e), body temperature (T_b), as well as insulation between smartphone and environment (k_e), and that between smartphone and body (k_b). P_p is thermal energy generated by smartphone per unit time. (right) World map (©OpenStreetMap contributors; openstreetmap.org) of locations of battery temperature readings (blue dots). Based on data collected by Android application OpenSignal from 25 April 2012 to 22 April 2013. Red ovals denote the eight cities for which air temperatures are estimated.

2. Data

[5] From the worldwide 1-year data set of 220 million battery temperature readings, a subset from eight major cities for half a year were selected, resulting in about 2.1 million readings. The cities cover a wide range of climate zones: Buenos Aires (Argentina), London (UK), Los Angeles (USA), Paris (France), Mexico City (Mexico), Moscow (Russia), Rome (Italy), and São Paulo (Brazil). They cover the period 7 May 2012 to 22 November 2012, which is divided in two periods: 7 May to 31 August (called summer, except for Buenos Aires and São Paulo, then called winter), and 1 September to 22 November (called autumn, except for Buenos Aires and São Paulo, then called spring). The temperature measurement only requires the application to be installed and the user to allow data collection. It does not require a data connection since data are cached on the device and uploaded periodically to a server for storage when a connection is available.

[6] After additional selections (see supporting information), 1.3 million battery temperature readings are left for further analysis, on average 844 per day and per city. Subsequently, those battery temperatures are averaged in space and time to obtain daily averaged (0–24 h local time) battery temperatures for each city.

[7] For each city, daily mean air temperatures (given as integers) from routine World Meteorological Organization certified stations were retrieved from the National Oceanic and Atmospheric Administration for calibration and validation purposes. All selected stations are located at airports, which are relatively close to the city center for Buenos Aires (5 km), London (12 km), Mexico City (7 km), Rome (7 km), and São Paulo (8 km). The stations of Los Angeles (18 km), Paris (22 km), and Moscow (27 km) are located further away from the city center. Note that the stations are at most representative for two local climate zones [Stewart and Oke, 2012] in the urban canopy layer. The observed air temperature data are utilized to calibrate a heat transfer model and for validation purposes.

3. Heat Transfer Model

[8] A smartphone is typically, although not always, carried in a pocket of clothing, close to the user’s body. The thermal energy generated by the smartphone must be balanced by heat outflow to the body and to the environment. The conductive heat flow between two adjacent systems is proportional to the temperature difference between the systems and depends on the thermal insulation between phone and environment and between phone and body. This law has been employed to derive a steady state heat transfer model to estimate daily averaged air temperatures from daily averaged battery temperatures for a unique combination j of city and sampling period (see supporting information for the derivation):

$$\bar{T}_{e,j,d}^{A,\text{day}} = m_j(\bar{T}_{p,j,d}^{A,\text{day}} - T_0) + T_0 + \epsilon_{j,d}, \quad (1)$$

where $\bar{T}_{e,j,d}^{A,\text{day}}$ is the daily averaged environmental or urban canopy layer air temperature, $\bar{T}_{p,j,d}^{A,\text{day}}$ is the daily averaged battery temperature (both in space A and time), and T_0 a constant equilibrium temperature. Note that m_j is a coefficient, $\epsilon_{j,d}$ is a random disturbance, and d denotes the day number.

[9] Using daily averaged observed air and battery temperatures, optimal values of m_j (for each city and period) and T_0 (constant for all cities and periods) are found employing least squares regression. One calibration and one validation data set are constructed for each city and period, by alternately assigning (without replacement) 1 day to the calibration and 1 day to the validation data set to avoid potential biases that may be induced by seasonal variations. The calibration data set is used to estimate the parameters of the heat transfer model (equation (1)), whereas the validation data set is used for verification of the performance of the heat transfer model on independent data. The optimal values of m_j for a certain city and period and the overall optimal value of T_0 are used to calculate air temperatures for the validation data set.

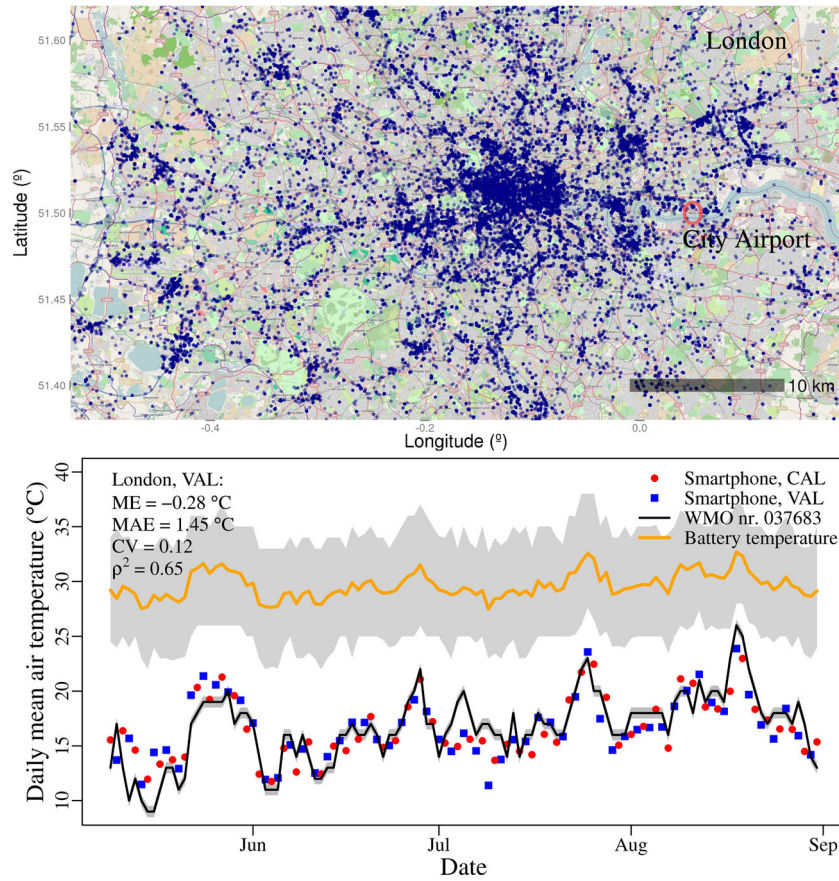


Figure 2. Estimation of air temperature from smartphone battery temperatures. (top) Map of London (UK; ©OpenStreetMap contributors; openstreetmap.org) showing locations of selected smartphone battery temperature readings (blue dots) from 7 May 2012 to 31 August 2012. Red oval indicates location of meteorological station at London City Airport. (bottom) Time series of daily averaged observed and estimated air temperatures, as well as battery temperatures in London for same period. Grey-shaded areas denote 10th to 90th percentiles of battery temperatures and ± 0.5 °C roundoff uncertainty in observed daily air temperatures. ME denotes mean error (bias), MAE is mean absolute error, CV is coefficient of variation and ρ^2 is coefficient of determination. CAL and VAL stand for calibration and validation data set, respectively. WMO nr. is World Meteorological Organization station index number.

4. Results and Discussion

[10] Air temperatures are estimated from battery temperature readings for eight cities. Figure 2 (top) shows the locations of selected battery temperature readings from

summer for London. Figure 2 (bottom) shows that daily battery temperature (orange line) and observed daily air temperature (black line) are strongly positively correlated (0.82), consistent with equation (1). The evolution of the estimated air temperatures often corresponds well with the

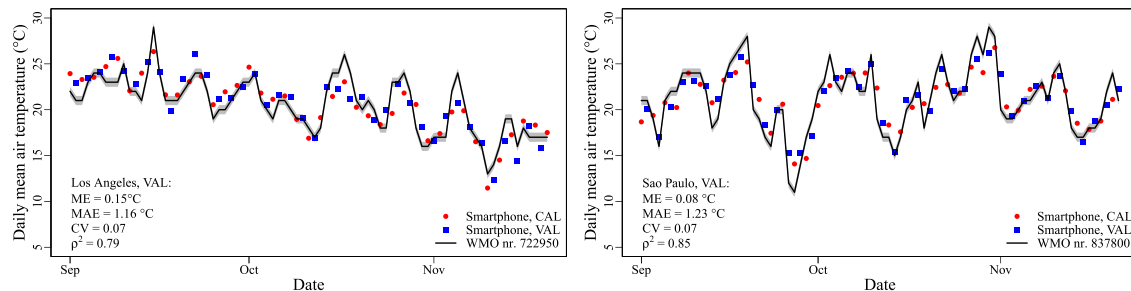


Figure 3. Time series of daily averaged observed and estimated air temperatures for 1 September 2012 to 22 November 2012. (left) For Los Angeles (USA). (right) For São Paulo (Brazil). Grey-shaded areas denote ± 0.5 °C roundoff uncertainty in observed daily air temperatures. ME denotes mean error (bias), MAE is mean absolute error, CV is coefficient of variation, and ρ^2 is coefficient of determination. CAL and VAL stand for calibration and validation data set, respectively. WMO nr. is World Meteorological Organization station index number.

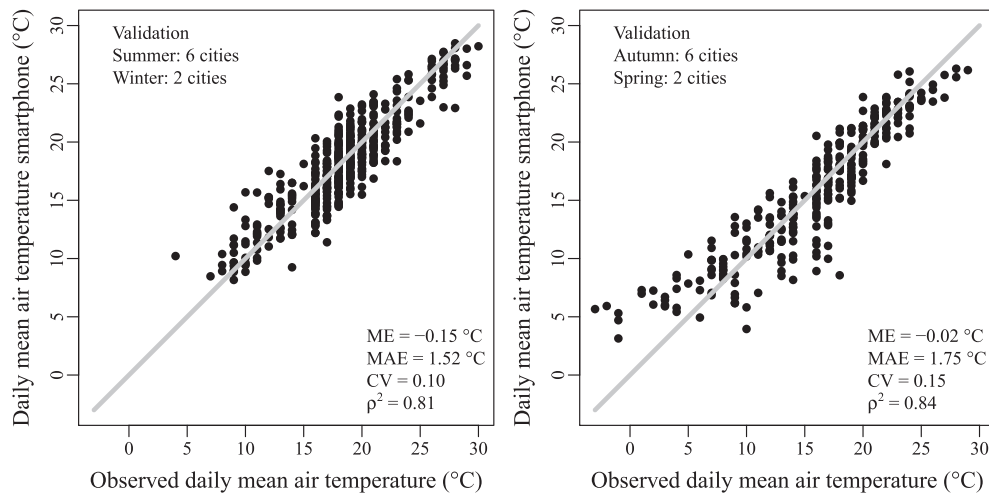


Figure 4. Validation of estimated daily air temperatures against observed daily air temperatures. (left) Scatter plot based on data from eight cities for 7 May 2012 to 31 August 2012. (right) Scatter plot based on data from eight cities for 1 September 2012 to 22 November 2012. Grey line is $y = x$ line. ME denotes mean error (bias), MAE is mean absolute error, CV is coefficient of variation, and ρ^2 is coefficient of determination. CAL and VAL stand for calibration and validation data set, respectively. WMO nr. is World Meteorological Organization station index number.

observations. Figure 2 (bottom) shows the estimated air temperatures for the calibration and the validation data sets. For the validation data set, the mean absolute error (MAE) of daily air temperatures amounts to 1.45°C , whereas the bias (ME) is only -0.28°C . The coefficient of variation (CV) (i.e., the ratio of the standard deviation of the differences to the mean daily observed air temperature) is 0.12 and the coefficient of determination (ρ^2) (i.e., the fraction of explained variance) is 0.65.

[11] Figure 3 shows results for Los Angeles (autumn) and São Paulo (spring), which are similar to London (summer). Alternating cold and warm periods are generally well estimated from the battery temperature data. Figures 2 and 3 are representative for the best obtained results. A more complete overview by scatter plots of daily air temperatures based on independent data from all cities and both periods (Figure 4) indicates a small bias. The coefficient of determination is large, 0.81–0.84, implying that a large part of the variation in observed daily air temperature can be explained by the estimated daily air temperature based on the heat transfer model (equation (1)). Nevertheless, deviations larger than a few degrees can be found. It appears that only for Paris and Moscow (autumn), the proposed model provides less accurate time series of daily air temperature, which is discussed in the supporting information. The time series for all cities and periods are given as Figures S3 and S4.

[12] An important problem is that a subset of battery temperature readings have likely been taken inside buildings or cars, whereas our goal is to observe outside air temperature. In addition, for each city and period, a constant value of m_j is assumed, while in reality each observation has its own thermal conductivity. One particular issue concerns representativeness errors. The smartphone battery and meteorological station observations represent temperature at different locations, where surrounding land use will generally differ as well. The battery temperature readings have been taken at many locations. Data from the meteorological stations are from one location for each city, which will not be

entirely representative for urban areas. Because of the complexity and diversity of local and microscale environments in a city, the estimated daily air temperatures will only provide a rough estimate of the actual areal average air temperature.

[13] The assumption that people carry their smartphone in a pocket in their clothing can be violated. Moreover, the number of received readings fluctuates during the day and between days and readings will therefore not always be representative to the same extent for estimation of daily averaged air temperatures. In addition, those influenced by outdoor air temperature fluctuate. For example, in case of cold periods, more people may stay inside, resulting in relatively high battery temperatures and hence overestimated air temperatures. See the supporting information for a more extensive discussion.

5. Conclusions and Perspective

[14] This study shows that it is possible to estimate relatively accurate daily urban canopy layer air temperatures from smartphone battery temperature readings employing a straightforward heat transfer model. By averaging over a sufficiently large number of battery temperature readings, the existing variation in thermal conductivity over individual readings is adequately filtered. Moreover, the influence of outside air temperatures is sufficiently reflected in the battery temperature readings, despite the fact that a subset of readings has likely been taken inside buildings. This proof of principle shows that monitoring air temperatures employing smartphones with an Android application holds great promise, although neither the application nor the smartphones have been designed for that purpose.

[15] Model coefficients would need to be optimized for different cities and seasons in order to provide worldwide air temperature estimates. In addition, operating system version, smartphone model, and screen size are likely to have an impact on the way in which the battery responds to air temperature. Coefficients of the heat transfer model

could therefore be optimized for, e.g., specific smartphone models, if sufficient data are available. Finally, techniques could be developed to detect whether the phone is indoors or outdoors, to select only those readings which have been taken outside.

[16] A substantial increase in the number of battery temperature readings from Android and iOS phones would allow for mapping urban air temperature to study the diurnal cycle and the urban heat island effect. This would require the selection of meteorological stations solely from densely populated urban areas for calibration. For example, dedicated urban meteorological networks may be used for this purpose [Muller et al., 2013], preferably a range of stations representative of the different microclimates. The diurnal variation in the coefficients of the heat transfer model should also be considered then. First, many additional high quality urban observations would be needed to refine the air temperature estimates from smartphones and to expand their possibilities. In the end, such a smartphone application could substantially increase the number of air temperature observations worldwide. This could become beneficial for precision agriculture, e.g., for optimization of irrigation and food production, for human health (urban heat island), and for energy demand planning.

[17] This work shows another opportunity of cellular communication networks to monitor the environment. Microwave links from these networks can be employed to measure rainfall [Messer et al., 2006; Leijnse et al., 2007; Overeem et al., 2011], or even to estimate the space-time dynamics of rainfall on a country-wide scale [Overeem et al., 2013]. Also dedicated sensors are being developed for smartphones, e.g., an add-on to measure aerosols [iSPEX, 2013]. The meteorological Phenomena Identification Near the Ground project enables users of a smartphone application to report information on precipitation near the ground [National Severe Storms Laboratory, 2013].

[18] Other opportunities may arise, e.g., some phones already have air humidity, air pressure, and air temperature sensors. OpenSignal has released a dedicated crowdsourcing weather application (WeatherSignal). Environmental data from smartphones could eventually even be utilized for data assimilation in numerical weather prediction models, development of urban canopy layer air temperature retrieval algorithms from satellites, water management, and urban planning. Hence, we expect that these projects and our results are only the beginning of crowdsourcing applications for measuring environmental variables.

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