Using remote sensing to quantify albedo of roofs in seven California cities, Part 1: Methods

George A Ban-Weiss^{a,b*}, Jordan Woods^b, Ronnen Levinson^b

^a Dept of Civil and Environmental Engineering
University of Southern California
3620 Vermont Ave KAP210
Los Angeles, CA 90089

^b Environmental Energy Technologies Division
Lawrence Berkeley National Laboratory
One Cyclotron Road
Berkeley, CA 94720

* Corresponding author:
George Ban-Weiss
Dept of Civil and Environmental Engineering
University of Southern California
3620 Vermont Ave KAP210
Los Angeles, CA 90089
banweiss@usc.edu
Phone +1 213 740 9124
Fax +1 213 744-1426

1 **Abstract**

2 Cool roofs reflect sunlight and therefore can reduce cooling energy use in buildings.
3 Further, since roofs cover about 20 – 25% of most cities, widespread deployment of cool
4 roofs could mitigate the urban heat island effect and partially counter urban temperature
5 increases associated with global scale climate change. The magnitude of these potential
6 benefits for a given city depends on the increase in albedo that can be achieved using
7 reflective roofs. Assessing this increase requires knowledge of roof albedo at the city-
8 scale, which until now has been unknown due to a lack of reflectance data with sufficient
9 spatial coverage, spatial resolution, and spectral information. In this work we use
10 multiband aerial imagery to derive the albedos of individual roofs in seven California
11 cities: Los Angeles, Long Beach, San Diego, Bakersfield, Sacramento, San Francisco,
12 and San Jose. The radiometrically calibrated, remotely sensed imagery has high spatial
13 resolution (1 m) and four narrow band reflectances: blue, green, red, and near-infrared.
14 First, we locate roof pixels within GIS building outlines. Next, we use laboratory
15 measurements of the solar spectral reflectances of 190 roofing products to empirically
16 relate broadband solar reflectance to reflectances in the four narrow bands; the empirical
17 relationship well predicts solar reflectance as indicated by a low root-mean-square of the
18 residuals of 0.016. Albedos computed from remotely sensed reflectances are calibrated to
19 ground measurements of roof albedo in each city. The error (accuracy) at 90% confidence
20 interval of the calibrated albedos is found to vary by city from 0.00 – 0.01 at low albedo
21 and 0.06 – 0.14 at high albedo.

22 **Keywords:** albedo; solar reflectance; cool roof; heat island effect

1. Introduction

Roofs cover the top of buildings, separating the atmosphere and the indoor environment. The solar reflectance or "albedo" of a rooftop is the fraction of incident solar energy that is reflected. Sunlight that is not reflected is instead absorbed by the roof; this energy is then transferred to the interior of the building and to the atmosphere. Dark roofs can have albedos as low as 0.05, meaning that they can absorb up to 95% of incident sunlight. Clean bright white roofs can have albedos above 0.90 (CRRC 2013), reflecting nearly all incident sunlight.

Monitoring studies have shown that replacing a dark roof with a white roof can decrease heat flows into the conditioned space, and lower cooling energy use. In many cases, cooling energy use reductions of 10 – 20% have been observed (Parker et al. 1995; Akbari et al. 1997; Parker et al. 1998; Akbari et al. 2001; Konopacki and Akbari 2001; Akbari 2003; Akbari et al. 2005). The cooling energy savings attainable for a particular building depends on its construction, roof and attic insulation, shade cover, and climate. In some situations, such as when roofs are thermally decoupled from the conditioned space, reflective roofs can have negligible effect on energy use (Ban-Weiss et al. 2013). Recognizing the potential energy and cost savings of white roofs, in October 2005 the California Energy Commission added to its Title 24 Building Energy Efficiency Standards (CEC 2005) a prescription that new or retrofitted low-sloped roofs on commercial buildings should generally be white. When the costs of white and dark roofs are approximately the same, reductions in energy costs translate directly to money saved. Note that while reflective roofs can increase heating energy use requirements in the

45 winter, summer cooling cost savings in most of California's climate zones far outweigh
46 this winter heating cost penalty (Levinson and Akbari 2010).

47 Solar reflective roofs have lower surface temperatures and thus transfer less heat to the
48 atmosphere than dark roofs. In most cases this reduced heat flow lowers surrounding air
49 temperatures. An observational study (Campra et al. 2008) showed that from 1983 –
50 2006, a region of southeastern Spain experienced near-surface air temperature decreases
51 of about 0.3 °C / decade as greenhouses with high albedo roofs were deployed. Since
52 roofs on average comprise about 20 – 25% of surface areas in North American cities
53 (Akbari et al. 1999; Akbari and Rose 2001a; Akbari and Rose 2001b; Akbari et al. 2003;
54 Rose et al. 2003; Akbari and Rose 2008), large-scale deployment of white roofs has been
55 suggested as a measure to mitigate the urban heat island effect (Taha et al. 1998; Akbari
56 et al. 1990; Akbari et al. 1992; Rosenfeld et al. 1995). Similarly, reflective roofs may
57 lessen urban temperature increases associated with global scale climate change. A remote
58 sensing study (Mackey et al. 2012) found that use of cool roofs in Chicago for reducing
59 urban heat islands has increased city-wide albedo and decreased roof surface
60 temperatures as detected by the LANDSAT satellite. Various mesoscale climate
61 modeling studies have simulated the climate effects of hypothetical increases in urban
62 albedo. For example, simulations reported by Taha (2008a) found 1 – 2 °C decreases in
63 peak urban temperatures at six locations in California. Other studies have shown
64 comparable temperature reductions in other regions (Synnefa et al. 2008; Taha 2008b;
65 Lynn et al. 2009; Zhou and Shepherd 2009). We note that one study showed that in some
66 situations urban air temperatures can rise with increased urban albedo (Taha 2008c); this

study hypothesized that the modeled temperature increase in Houston, Texas was due to reduction of the atmospheric mixing height.

Other modeling studies have investigated the effect of increasing urban albedo across the United States (Millstein and Menon 2011) and globally (Akbari et al. 2009; Menon et al. 2010; Oleson et al. 2010; Jacobson and Ten Hoeve 2012; Akbari and Matthews 2012; Akbari et al. 2012; Cotana et al. 2014). Millstein and Menon (2011) used a regional climate model to show that adopting cool roofs and pavements in urban areas of the United States could reduce afternoon summertime temperatures in urban locations by 0.1 – 0.5 °C. A study using a global climate model (Oleson et al. 2010) demonstrated that reflective surfaces could decrease the annual mean urban heat island effect¹ to 0.8 °C from 1.2 °C.

While reflective surfaces have been modeled in most situations to reduce urban temperatures, their effects on the hydrological cycle also warrants investigation. One mesoscale climate modeling study (Georgescu et al. 2012) has suggested that reflective surfaces may reduce precipitation around Phoenix, Arizona. Since Phoenix has unique desert meteorology with most of its precipitation arriving with late-summer monsoon thunderstorms, this result may not hold in other regions.

Determining realistic estimates of the potential for increasing roof albedo at the city scale requires detailed understanding of the current stock of roofs. Currently there are no estimates of the mean urban roof albedos. There are at least five challenges associated with quantifying roof albedo at the city scale: spatial coverage, spatial resolution, spectral

¹ The urban heat island effect was defined by Oleson et al. (2010) as the difference (urban – non-urban) in 2-m air temperature between urban and non-urban portions of model grid cells.

88 coverage, radiometric calibration, and cost. For example, roof albedo can be accurately
89 measured at the rooftop by using a pyranometer to measure incident and reflected
90 (bihemispherical) sunlight (ASTM 2006). However, measuring a sample large enough to
91 statistically represent the roofs of a city is logistically prohibitive. Remote sensing can
92 rapidly characterize large geographic areas. For example, there exist freely available
93 surface albedo datasets derived from satellite sensors like MODIS (Schaaf et al. 2002;
94 Schaaf 2004). Data are available describing both directional-hemispherical reflectance
95 (referred to as “black-sky” albedo) and bihemispherical reflectance (referred to as white-
96 sky albedo). However, its spatial resolution of 500 m (16-day composites) is too low to
97 distinguish various urban surface types such as roofs. Imagery from commercial satellites
98 (e.g., GeoEye, IKONOS) offers spatial resolutions on the order of 1 m and spectral
99 information in the visible and near-infrared (near-IR). While the spatial resolution and
100 spectral coverage may be sufficient to distinguish roofs and compute roof albedo,
101 purchasing these imagery for entire cities would be costly. As of 2014, minimum costs
102 for these data are roughly US\$15 per km², so acquiring imagery for only the City of Los
103 Angeles would be about \$20,000, and for the entire metropolitan area of Los Angeles
104 about \$200,000. Another option is aerial imagery, which is often acquired from aircraft.
105 Since these aircraft are generally nearer to the ground than satellites, the captured
106 imagery is at higher spatial resolution. While aerial imagery can sometimes provide
107 multiband information in the visible and near-IR, it is almost always acquired for
108 generating photographs and therefore does not provide the calibrated radiance data
109 needed for scientific analysis. To overcome the aforementioned challenges associated
110 with spatial coverage of ground measurements, cost and spatial resolution of satellite

data, and radiometric limitations of most aerial imagery, we acquired high-resolution, radiometrically calibrated, aerial imagery for the purpose of deriving roof albedos.

In this paper we develop a method for using radiometrically calibrated aerial imagery to estimate roof albedos for seven cities in California: Los Angeles, Long Beach, San Diego, Bakersfield, Sacramento, San Francisco, and San Jose. The aerial imagery has high spatial resolution (1 m) and includes reflectances in four narrow spectral bands: three in the visible (blue, green, and red), and one in the near-infrared. The near-IR contains approximately 50% of the energy from the sun (Levinson et al. 2010). Some “cool roofs” have low reflectance in the visible spectrum but high reflectance in the near-IR spectrum, allowing the roof to remain dark while increasing its albedo (Levinson et al. 2007). Thus, having information about reflectance in both the visible and near-IR spectra improves estimates of roof albedo. The work is presented in two parts. In Part 1 (this paper), we present methods for calculating roof albedo from remotely sensed reflectances, and show sample results. Part 2 (a companion paper, Ban-Weiss et al. submitted) reports roof albedos in each of the seven California cities of interest. It also provides further analyses and applications using the albedo dataset. Applications include use of roof albedos in a regional climate model to estimate temperature decreases attainable by converting the current stock of roofs to solar reflective cool roofs. This work is a first attempt to quantify the albedos of individual roofs at the scale of entire cities.

2. Methods

In this section we describe the methods developed to derive the albedos of roofs in seven California cities: Los Angeles, Long Beach, San Diego, Bakersfield, Sacramento, San

Francisco, and San Jose. Figure 1 diagrams the approach. Reflectances in narrow bands denoted blue, green, red, and near-IR were obtained from high spatial resolution (1 m) imagery acquired using airplanes during summer 2009. We refer to the data collected using the airplane as “remotely sensed.” Pixels containing roofs were then extracted from the imagery. Roof pixels were identified using GIS building outline datasets for entire cities where available. When building outline datasets were not available, manual tracing of buildings was performed. Laboratory measurements of the solar spectral reflectances of 190 roofing products were used to empirically relate solar reflectance to reflectances in the four narrow bands. Remotely sensed solar reflectances were calibrated to ground measurements of roof albedo in each city. Pixels within each roof boundary were then averaged to calculate the mean albedo of each roof. Note that we define albedo consistently with the “cool roof” scientific community as the ratio of reflected to incident broadband solar radiation, and subsequently specify the illumination-viewing geometry for each measurement. Each step is now described in more detail.

2.1. Data source

The aerial imagery was originally acquired for the National Agriculture Imagery Program (NAIP), which is administered by the US Department of Agriculture (USDA). NAIP annually acquires aerial imagery during the agricultural growing season (late spring to early summer) in the continental United States. One of the main goals of NAIP is to provide digital ortho photography to government agencies and the public. While this program is focused on agriculture, imagery is generally acquired for entire states including urban areas. NAIP has strict requirements to ensure high image quality. For example, to minimize shadows, flights must occur when the sun is at least 30 degrees

above the horizon. In practice, all imagery is collected when the sun is at least 60 degrees above the horizon. Flights must acquire imagery on clear days without cloud cover (NAIP 2013).

NAIP imagery is available for the entire state of California at 1 m spatial resolution in years 2005, 2009, 2010, and 2012 (NAIP 2013). NAIP contracts different companies to acquire imagery each year. As such, various imagery acquisition systems have been used. In 2009, imagery for California was collected by North West Group (Calgary, Alberta, Canada) using a Leica ADS80/SH82 airborne digital sensor (Leica 2013). This sensor is more than a high-speed digital camera for photography. It utilizes arrays of digital charge-coupled devices that sense light in four narrow spectral bands (blue, 420 – 492 nm; green, 533 – 587 nm; red, 604 – 664 nm; and near-IR, 833 – 920 nm). The arrays of detectors are arranged perpendicular to the flight direction in a “push broom” configuration. Each detector is radiometrically calibrated in the laboratory to accurately measure radiance in its spectral band. Thus, the sensor accurately measures multi-spectral radiance, similar to that acquired by sensors on satellites for scientific applications. In this way, the imagery collected by the sensor has the potential to be used as a scientific remote sensing data set, rather than simply as photographs. NAIP imagery is publically available as either “digital ortho quarter quad tiles” (DOQQs) or “compressed county mosaics” (CCM); both options include imagery compression, a variety of color adjustments, and other post-processing required by NAIP (NAIP 2013). This post-processing improves the overall appearance and usability of the imagery, but destroys the radiometric calibration, which is important for the purposes of this study. Therefore, we acquired directly from NAIP’s vendor for 2009 (North West Group) the radiometrically

calibrated radiance data for images within our cities of interest. The field of view of the sensor resulted in image footprints that are 12 km wide (perpendicular to flight direction), and of varying length depending on flight paths. The mean altitude of the flights was about 9 km above ground level, leading to view zenith angles for the line scanner up to about 34°. Each flight strip has 15% overlap with the adjacent flight strip corresponding to view zenith angles of 30° to 34°; thus, about 30% of the area for each city has duplicate imagery.

2.2. Correcting for the atmosphere and surface reflectance anisotropy

Since we are interested in reflectance at Earth's surface, the radiance measurements at the sensor (on the airplane) needed to be corrected for atmospheric scattering and for surface reflectance anisotropy. Techniques have been previously developed and described at length elsewhere, so we provide only a brief description here.

Atmospheric gases and particles can influence the perceived "at-sensor" radiance through multiple pathways (Schaepman-Strub et al. 2006; Downey et al. 2010). The atmospheric correction allows for estimating surface reflectance by isolating (a) the radiance that originates from the Earth surface, and (b) the solar spectral irradiance at the surface. The surface spectral reflectance, a characteristic of the coupled surface-atmosphere system, is a function of the measured at-sensor radiance, the mean solar spectral irradiance at the top of atmosphere (TOA), the path radiance over an absorbing surface (i.e., the "dark pixel" radiance from downwelling sunlight that is reflected by the atmosphere into the sensor before having reached the surface), the total downward transmittance from the TOA to the ground, the total upward transmittance from the ground to the sensor, and the spherical albedo of the atmosphere (i.e., the fraction of upward radiance that is then

backscattered by the atmosphere) (Kaufman and Sendra 1988, Fraser et al. 1992). The first term, at-sensor radiance, is measured. The second term, TOA mean solar spectral irradiance, can be computed from the solar constant as a function of the cosine of the solar zenith angle. The latter four unknown terms are estimated using a modified Song-Lu-Wesley method (Song et al., 2003, Downey et al. 2000), which is based on a linear parameterization similar to that used by the Advanced Very High Resolution Radiometer (AVHRR) satellite sensor. The atmospheric reflectance for each view and sun zenith angle is first estimated using expected versus measured surface reflectances for dark pixels. The four unknown parameters are then determined for each spectral band based on parameterizations derived from atmospheric modeling performed for various flying heights, ground elevations, sun and view zenith angles, and atmospheric reflectances. Past studies have validated the atmospheric correction by comparing to ground reflectance measurements (Beisl and Adiguezel 2010; Markelin et al. 2010) and found agreement to within 10%.

The correction accounting for surface reflectance anisotropy is based on a modified Walthall method (Beisl et al. 2008, Downey et al. 2010). Since flights for NAIP are always in the north-south direction, the correction minimizes spurious east-west gradients in reflectance (i.e., perpendicular to the flight direction). The method is semi-empirical and the sum of “kernels” accounting for incident illumination zenith angle, reflection view zenith angle, relative azimuth angle (Nilson and Kuusk, 1989), and an additional “hot spot” term based on the distance function of the Li-kernels from the AMBRALS model (Wanner et al. 1995). The correction in part uses summary statistics for land pixels

at equal viewing zenith angles and masks water so that specular reflection does not influence results (Downey et al. 2010).

Strictly speaking, the resulting reflectances described here are hemisphere-directional reflectance factors (HDRF), using the naming conventions described by Schaepman-Strub et al. (2006). In this investigation we aim to derive bihemispherical reflectances (BHR). The most physical methods for deriving BHR from HDRF require either knowledge of the Bidirectional Reflectance Distribution Function (BRDF) for each roofing material, or many aerial images for each location at a variety of viewing angles. Because we have neither, we use rooftop measurements of BHR to ‘calibrate’ HDRFs (see Section 2.5). Such a calibration is justified by the high correlation observed between HDRF and BHR for vegetation canopies, shown in Figure 4 of Schaepman-Strub et al. (2006); we expect even higher correlation for roofing materials given that their surfaces are generally more isotropic than natural vegetative surfaces. While this simplification contributes to the errors later discussed in Section 3.2 and reported in Table 3, we note that differences between HDRF and BHR are generally small. For example, for vegetation canopies, the absolute difference between these two metrics is < 0.02 , with relative differences up to 14%, which is tolerable for the purposes of our study (Schaepman-Strub et al. 2006). Because of the reduced anisotropy of roofs, differences are expected to be lower for roofs than vegetation. Errors introduced by this simplification are explored in Section 4.2, which compares albedos for buildings with duplicate values computed independently using two different view zenith angles (about $\pm 30^\circ$ versus $\pm 30^\circ$).

Surface reflectances (HDRFs) are reported for each of the four narrow bands in each 1 m pixel; we refer to these as the remotely sensed blue, green, red, and near-infrared reflectances. Figure 2 shows example imagery for the four narrow bands in a portion of San Jose, California. Low reflectance pixels in each narrow band are dark, and high reflectance pixels are white. (Note that the line of trees on the right side of the image shows higher reflectance in near-IR than in the red, a characteristic of light reflection from leafs (Slatton et al. 2001).) The remainder of the method sections describe our derivation of roof albedo (i.e. broadband solar reflectance) from these narrowband reflectances (Figure 2).

2.3. Extracting roof pixels from the imagery

Next we identify in the imagery pixels containing roofs. For five of the seven cities of interest (Los Angeles, Long Beach, Bakersfield, San Francisco, and San Jose), shapefiles containing outlines for every building within the city were acquired from local governments (Table 1). Example building outlines projected onto a red-green-blue (RGB) composite of the aerial imagery in San Jose are shown in Figure 3a. The building outlines include detailed features of each building, as can be better observed when projected onto higher spatial resolution (but not radiometrically calibrated) imagery from United States Geological Survey (USGS) (Figure 3b). In our analysis we assume that building outlines and roof outlines are colocated.

In the two cities for which we could not acquire building outlines (Sacramento and San Diego), we manually traced the edges of buildings in the imagery using ESRI ArcMap 10.0. Manually tracing perfect outlines proved difficult. We therefore intentionally traced outlines that were slightly within the actual building borders, ensuring that non-

roof pixels were not included within the boundaries. Manually tracing every building was not feasible, so we traced a small but statistically representative sample of buildings within each of these two cities. To determine the number of buildings needed to properly characterize the mean roof albedo of a city, we performed a Monte Carlo statistical investigation using the population of albedo values computed for Los Angeles. As shown in our companion paper (Ban-Weiss et al. submitted), 1000 roof outlines was found to be sufficient. Hundreds of 300 x 300 m² quadrats (small, typically rectangular study regions) were generated in random locations within city boundaries; all roofs within the borders of the quadrats were traced until the minimum number of outlines ($N=1000$) was met. An example of manually traced outlines within a quadrat in Sacramento is shown in Figure 3c.

2.4. Relating broadband solar reflectance (albedo) to narrowband reflectances

To quantify the albedo of individual roofs, we need a method to relate broadband solar reflectance to the four (narrowband) remotely sensed reflectances. In this section we describe this spectral conversion. We note again that we use “albedo” to mean broadband solar reflectance without regard to the angular characteristics of incoming and reflected light; these geometries are instead described for each measurement. (This naming convention is consistent with that of the cool roof scientific community, but is inconsistent with that of the remote sensing community, which reserves albedo to mean bihemispherical reflectance (Schaepman-Strub et al. 2006).) We began by computing the solar, visible, and narrowband (blue, green, red, and near-IR) reflectances of each of 190 roofing products from laboratory measurements of solar spectral reflectance. Included in the 190 samples were all widely used roofing types in California for both commercial and

residential buildings (Table 2). Samples were new and mostly acquired from various roofing supply stores in the San Francisco Bay area. Clay tile samples were provided by MCA Superior Clay Roofing Tiles. While use of roofing materials that had been aged outdoors was desired, it was infeasible to collect soiled roofing materials. Solar spectral reflectance was measured using a PerkinElmer Lambda 900 UV/Vis/NIR spectrophotometer equipped with a 150-mm Labsphere integrating sphere. Spectral reflectances were measured from 300 to 2500 nm in 5 nm steps. All measurements are of near-normal (8°) beam-hemispherical reflectance (a.k.a. directional-hemispherical reflectance using the naming convention of Schaepman-Strub et al.) following ASTM Standard E903-12.

Figure 4 shows the solar spectral reflectance, $\rho(\lambda)$, of several roofing products, as well as the solar spectral irradiance, $j(\lambda)$, used to compute band reflectances. This air mass one global horizontal (AM1GH) terrestrial irradiance assumes a clear sky and the sun at zenith, and is suited to characterizing roof solar reflectance (Levinson et al. 2010). Irradiance-weighted band reflectance R over each range of interest was calculated as

$$R = \frac{\int_{\text{range}} j(\lambda)\rho(\lambda)d\lambda}{\int_{\text{range}} j(\lambda)d\lambda}. \quad (1)$$

We computed four narrowband reflectances—blue, b (420 – 492 nm); green, g (533 – 587 nm); red, r (604 – 664 nm); and near-IR, i (833 – 920 nm)—and three broadband reflectances: visible, V (400 – 700 nm), near-IR, I (700 – 2500 nm), and solar, S (300 – 2500 nm). (Narrowband spectral ranges correspond to those of the remote sensor.

Lowercase symbols represent narrowband reflectances and uppercase symbols represent broadband reflectances.) Note that while the narrow blue, green, and red spectra collectively span most of the visible spectrum, the narrow near-infrared spectrum used to compute i spans less than 5% of the full near-infrared spectrum (700 – 2500 nm) (Figure 4). Hence, we expect (b, g, r) to predict V more accurately than (b, g, r, i) can predict S .

Using the aforementioned laboratory measurements we developed empirical relationships between broadband and narrowband reflectances using multivariate regression. We first modeled $V = V(b, g, r)$ to test the method, then modeled $S = S(b, g, r, i)$.

2.5. Calibrating remotely sensed values using ground truths

To calibrate the remotely sensed values, we measured the albedos of several roofs in each city, and then evaluated $S(b, g, r, i)$ for these roofs using remotely sensed b, g, r , and i .

Measured albedos were obtained using one of two methods. In the first, we identified buildings that had new roofs installed within six months prior to the flights. The make and model of the new roof was known, allowing us to obtain its albedo from an online database (CRRC 2013). In the second, we measured rooftop albedos with a pyranometer.

The pyranometer measurements were performed in July 2012 in San Jose and Los Angeles, and in September 2012 in San Francisco and Davis (near Sacramento). Since these measurements were taken about three years after the imagery was acquired via airplane, the second method was implemented only for roofs with low measured albedos ($S < 0.4$); as shown in Sleiman et al. (2011), aging (i.e., weathering and soiling) had a small effect on the albedo of such roofs in this range. White roofing products can show

marked decreases in albedo after three years (Sleiman et al. 2011) and were therefore not included in this second method.

Method 1 (applied to all roofs). Several roof manufacturers and vendors identified the make and model of roofs installed in each city no more than six months prior to each flight. The initial solar reflectance of each installed roof was then obtained from the Rated Products Directory of the Cool Roof Rating Council (CRRC 2013). Corresponding remotely sensed albedos were then quantified by randomly sampling 10 pixels within the roof boundary. Only pixels with visible roofing material were included; HVAC equipment, solar photovoltaics, skylights, and other features were excluded. In total, 31 buildings with known installation dates and roofing product types were used.

Method 2 (applied only to roofs with low measured albedo). We measured the albedo of roofs on 10 buildings in (or very near) four of the seven cities with a Kipp & Zonen CMA6 first-class albedometer, which integrates back-to-back a pair of Kipp & Zonen CMP6 first-class pyranometers. In situ roof albedos were measured following ASTM Standard E1918-06, “Standard Test Method for Measuring the Solar Reflectance of Horizontal and Low-Sloped Surfaces in the Field” (ASTM 2006), which determines bihemispherical solar reflectance with solar beam incidence angle $< 45^\circ$. Three consecutive albedo measurements were performed at each of three locations on each roof, for a total of nine measurements per roof. The mean albedo was calculated by averaging these nine measurements. Corresponding remotely sensed albedos were extracted by identifying each measurement location in the imagery; the mean value of pixels within a 3 m radius was calculated to approximate the field of view of the pyranometer. This was done for each of the three measurement locations per roof. The three resulting albedos

357 were then averaged and compared to the measurement-derived mean albedo for each
358 roof.

359 We were unable to obtain measurements for low albedo roofs in Bakersfield using either
360 Method 1 or 2. Instead, we obtained from Bakersfield Public Works records of asphalt
361 concrete pavement installations. Two roads were paved within one year prior to the
362 flights; installations were 3 weeks and 8 months prior to the flights, respectively.
363 Associated albedos were assumed to be 0.05 and 0.07, respectively, derived from
364 measurements of the post-installation time evolution of asphalt pavement albedo
365 (unpublished). Corresponding remotely sensed values were obtained using the random
366 sampling technique described above for Method 1.

367 Measured albedo, S_{measured} , was regressed to remotely sensed albedo, $S(b, g, r, i)$, using a
368 power law relationship of the form

$$S_{\text{measured}} = a_c S^{p_c} \quad (2)$$

369 This was done separately for each city to determine parameters a_c and p_c , where
370 subscript c indexes the seven cities. These power law parameters were then used to
371 determine the calibrated remotely sensed (pixel level) albedo S' in each city as

$$S' = a_c S^{p_c} \quad (3)$$

372 where the prime indicates “calibrated.” The error ε (accuracy) of the remotely sensed
373 albedos (S') in each city was then estimated using the standard errors of the power law
374 parameters. Upper and lower-bound estimates of the coefficients were derived as mean

375 value $\pm 90\%$ confidence interval. One-sided confidence intervals above (ε^U) and below
 376 (ε^L) the mean were then calculated as a function of calibrated albedo as

$$\varepsilon^U(S') = a_c^U S'^{p_c^U} - S' \quad (4)$$

$$\varepsilon^L(S') = S' - a_c^L S'^{p_c^L} \quad (5)$$

377 where superscripts U and L correspond to upper- and lower-bound parameter estimates.
 378 These error estimates indicate the accuracy with which calibrated albedos are calculated
 379 from uncalibrated remotely sensed values. Note that we present one-sided confidence
 380 intervals because the power law form of Eq. (3) makes ε asymmetric about S' .

381 White roofs are commonly single-ply (plastic) membranes or elastomeric coatings, both
 382 of which are very smooth and glossy when new. Reflection from these materials can
 383 therefore include a non-negligible specular component at high angles of sunlight
 384 incidence (e.g., see Levinson et al. 2010). Since white roofs are almost always low-slope
 385 and flights occurred with the sun at least 60° above the horizon, we expect in most cases
 386 that the specular component of reflection will be negligible. However, some commercial
 387 roofs can be “wavy” and have areas with high pitch, making the incidence angle large
 388 and introducing a non-negligible specular reflection. Such instances were seen in the
 389 remotely sensed data as widely varying pixel-level roof albedos within the boundaries of
 390 a roof, and were more likely to occur near the edges of flight strips. To ensure that roofs
 391 used for calibration had negligible specular reflection reaching the aerial sensor, we
 392 omitted buildings that (a) were near the flight strip edges, and (b) contained pixel-level
 393 albedos within the roof boundary that varied by more than 0.1.

2.6. Mean albedo for each roof

Mean albedos for each roof were calculated by averaging S' within each building outline. Some non-roofing materials were included since roofs can house HVAC equipment, skylights, solar photovoltaics, and other features. While we expect such equipment to minimally affect the mean roof albedo for each city, it can strongly affect the albedo of individual roofs. To estimate the magnitude of this effect, we used high-resolution imagery from USGS (see Section 2.3 and Figure 3b) to compute the fraction of roof area covered by non-roof elements for 150 randomly selected buildings in Los Angeles. On average, non-roof elements were found to cover 2% of the footprint area for these roofs. Buildings with low-slope roofs in many cases had a higher fractional coverage by non-roof elements, but these buildings make up a relatively small fraction of the total population of buildings in a city (see Ban-Weiss et al. submitted).

2.7. Precision of the remotely sensed albedos

As was mentioned in Section 2.1, about 30% of each city has overlapping imagery and therefore two values of remotely sensed roof albedo. For each city, duplicates were used to determine the precision error calculated as the scaled arithmetic difference,

$$\text{Scaled arithmetic difference} = \frac{(S'_2 - S'_1)}{\sqrt{2}} \quad (6)$$

where subscripts 1 and 2 describe each duplicate value. Note that there is imprecision in each value S'_1 and S'_2 ; since these imprecisions add quadratically, we divide by $\sqrt{2}$ in Eq. (6) to determine the precision of one measurement (Hyslop and White 2009). Each of

the duplicates compares albedo computed using data obtained at two different view
zenith angles (-34° to -30° versus $+30^\circ$ to $+34^\circ$) and solar zenith angles (see Section
2.1).

3. Results

3.1. Obtaining solar reflectance (broadband) from remotely sensed (narrowband) reflectances

We modeled $V = V(b, g, r)$ using the simple linear form

$$V_k = c_b b_k + c_g g_k + c_r r_k. \quad (7)$$

Here V_k , b_k , g_k , and r_k are band reflectances computed from Eq. (1); each c is a fitted
coefficient; and subscript k indexes the 190 roofing samples. This linear model with
 $c_b = 0.37$, $c_g = 0.30$, and $c_r = 0.31$ predicts V with a coefficient of determination $R^2 =$
0.99. Figure 5a evaluates the empirical model by comparing $V(b_k, g_k, r_k)$ to V_k . The
minimal deviation of points from the one-to-one line indicates that the linear model well
predicts V . A histogram of residuals (Figure 5b) shows that the linear model can predict
 V to within 0.02; the root mean square (RMS) error χ is 0.003. Adding higher order
terms and/or cross products to Eq. (7) did not improve the fit.

Next we attempted to quantify solar reflectance as

$$S_k = c_b b_k + c_g g_k + c_r r_k + c_i i_k. \quad (8)$$

The linear model with $c_b = 0.17$, $c_g = -0.13$, $c_r = 0.33$, and $c_i = 0.54$ predicts S with $R^2 =$
0.99. Figure 5c evaluates the empirical model by comparing $S(b_k, g_k, r_k, i_k)$ to S_k .

Again, there is minimal deviation from the one-to-one line, showing that the linear model well predicts S . More complicated variants to Eq. (8) were evaluated, this time including a term equal to the normalized difference vegetation index (NDVI).² The more complex models were found to be no better than the simple linear equation (Eq. (8)). A histogram of residuals is shown in Figure 5d. The linear model can predict S with an RMS error of 0.016.

The largest outlier is a metal roofing sample (zincalume with clear resin finish) in which $S(b_k, g_k, r_k, i_k)$ underpredicts S_k by 0.10. Figure 4 shows the spectral reflectance of this outlier. It can be seen that the narrowband near-IR spectral range does not capture the increased reflectance at $\lambda > 1000\text{nm}$; thus, i (833 – 920 nm) underpredicts broadband near-IR reflectance (700 – 2500 nm). A roofing product with strongly varying spectral reflectance in the near-IR may not always be well characterized by the narrowband near-IR reflectance i .

3.2. Calibrating remotely sensed values using ground truths

Figure 6 shows measured versus remotely sensed (uncalibrated) albedos for the buildings that served as ground truths. Results for the City of Los Angeles and Long Beach are shown together since they are both part of the Greater Los Angeles Area. For low measured albedo ($S < 0.4$) most remotely sensed values are near measured values, while for high measured albedo ($S \geq 0.4$), the discrepancy is larger. Remotely sensed albedos

² NDVI is a metric that is often used to determine whether pixels contain live vegetation, and is calculated as $(I - V)/(I + V)$. Live vegetation characteristically has higher near-IR reflectance than visible reflectance and therefore $\text{NDVI} > 0$. The use of NDVI in this study was an attempt to identify cool roofs with low reflectance in the visible but high reflectance in the near-infrared. While the metric successfully identified cool colored roofs, adding it as a term to Eq. (8) did not improved the empirical model.

are consistently lower than measured values.. To derive remotely sensed (calibrated) albedos, the equations for each city shown in Figure 6 were applied to the uncalibrated values.

Table 3 shows an estimate of the error (accuracy) at 90% confidence interval of the calibrated remotely sensed albedos. Error was calculated using Eqs. (4) and (5). Low albedo values are quite accurate, while high albedo values are generally less accurate. Note that the error for high albedo values is smaller in San Jose than in the other cities because we had a relatively high number ($N=8$) of high albedo measurements, all of which had consistent remotely sensed values. The reported errors represent the estimated accuracy associated with the mean value for a given roof. However, the relatively large error for high albedo roofs does not markedly influence the mean roof albedo for each city since high albedo roofs comprised a small fraction of total urban roof area in 2009. There may exist individual high albedo roofs that have errors larger than reported (i.e., outside the 90% confidence intervals) because of an increased contribution of specular reflectance. These outliers would most commonly have newly installed high albedo roofs with “curvy” roof shapes. The curves in the roof would mean that certain areas have high incidence angles and therefore significant specular reflectance (see Section 2.5 and 4.1).

3.3. Maps of roof albedo

Figure 7 shows a zoomed in area of San Jose with the mean value of calibrated albedo S' for each roof. As expected in California due to Title-24 Building Energy Efficiency Standards (CEC 2005), some commercial buildings with large flat roofs have high albedo. Homes with pitched roofs usually have low albedo roofs. Our companion paper

(Ban-Weiss et al. submitted) shows city-wide results for all seven cities and provides further analysis.

4. Discussion and Conclusions

4.1. Errors in computed albedo introduced by roof slope.

In this study we do not account for the dependence of irradiance on roof slope. This simplification could lead to inaccuracies in remotely sensed albedo since it is the ratio of reflected to incident sunlight. We estimate the magnitude of the error from this simplification using results from Levinson et al. (2010) that quantify the dependence of hemispherical (direct + diffuse) solar irradiance on roof pitch as a function of solar zenith angle (z). In Levinson et al., pitched roofs were approximated by the curved wall of a right circular cone since the population of pitched roof planes have no preferred azimuth orientation. In California, most pitched roofs have slope $\leq 23^\circ$ (rise over run = 5:12), which we used as our pitched roof case for this error estimate.

Assuming $z = 0^\circ$, hemispherical irradiance (I_h) on an axisymmetric surface with a 5:12 pitch is $I_h = 1030 \text{ W m}^{-2}$, or 5.5% less than that on a horizontal surface ($I_h = 1090 \text{ W m}^{-2}$).

Assuming $z = 30^\circ$, the maximum zenith angle during the flights that acquired the aerial imagery, I_h is 875 W m^{-2} for a roof pitch of 5:12, or 6.4% less than that on a horizontal surface ($I_h = 935 \text{ W m}^{-2}$). Therefore, for $z \leq 30^\circ$ we may have overestimated solar irradiance by up to about 6%, leading to underestimates for albedo of about 6%.

4.2. Precision error

The errors introduced by simplifications in viewing geometry (Section 2.2) and roof pitch (Section 4.1) used in this study can be explored by comparing the computed albedos

derived for buildings with overlapping imagery and therefore two remotely sensed values (see Section 2.7). Regions with duplicate albedos are generally at flight strip edges with corresponding view zenith angles of (a) -34° to -30° , and (b) $+30^\circ$ to $+34^\circ$. Solar zenith angles also generally vary for each of the duplicate values, though there is no consistent difference among flight strips. If the aforementioned simplifications introduced appreciable error, one would expect the duplicate remotely sensed albedos for a given building to be markedly different. The full precision analysis is presented in the companion paper (Ban-Weiss et al. submitted), but as an example result for one of the cities investigated here, the 430,332 buildings in Los Angeles with independently computed duplicate albedos showed an RMS scaled arithmetic difference (Eq. 6) of 0.02, suggesting the simplifications discussed here lead to small errors for most roofs.

4.3. Summary

In this paper we have presented a method for deriving the mean albedo of individual roofs in California using aerial imagery (Figure 1). The imagery (Figure 2) was acquired on an airplane at high spatial resolution (1 m) in four spectral bands (three in the visible and one in the near-IR) using a radiometrically calibrated sensor. Including the near-IR band is important for quantifying roof albedo since (1) some “cool roofs” have low reflectance in the visible but high reflectance in the near-IR, and (2) about 50% of the energy from the sun is in the near-IR part of the solar spectrum. We have developed methods for (a) identifying building outlines (Table 1, Figure 3), (b) converting the four narrowband reflectances to solar reflectance (albedo) based on laboratory measurements of solar spectral reflectance for 190 roofing products (Table 2, Figure 4, Figure 5), and (c) calibrating remotely sensed albedos by comparing to measured albedos of several

roofs in each city (Figure 6). We have found our method to be quite accurate for most roof types in California, while errors in computed albedos are relatively large for high albedo roofs that are presumably new and white (see Table 3). For example, roofs with an albedo near 0.2 had estimated errors (one-sided, 90% confidence intervals) ranging from 0 to 0.02, varying by city. On the other hand, roofs with an albedo near 0.8 had corresponding errors ranging from 0.05 to 0.12. The method was also shown to be precise. Precision error, computed using duplicate albedo values for roofs in flight overlap areas, was found to be 0.02 for Los Angeles (see Section 4.2). Each duplicate albedo was derived using remotely sensed data with differing viewing and illumination geometries.

In our companion paper (Ban-Weiss et al. submitted), we present city-wide albedo results for our seven California cities of interest, report results of the precision analysis for all analyzed cities, and provide additional analyses based on the city-wide results. We also use the roof albedo results for Bakersfield as an input to a regional climate model to predict the summer and winter temperature and precipitation changes that could result from converting the current stock of roofs to cool roofs.

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Table 1. Sources of shapefiles containing outlines of all buildings within five of the seven cities of focus. Outlines were not available in Sacramento and San Diego.

City	Source
San Jose	City of San Jose (2011)
San Francisco	City and County of San Francisco (2011)
Bakersfield	City of Bakersfield (2011)
City of Los Angeles	Los Angeles Region Imagery Acquisition Consortium 3 (2011)
Long Beach	Los Angeles Region Imagery Acquisition Consortium 3 (2011)

Table 2. Roofing samples for which we measured solar spectral reflectances in the laboratory.

Roofing product type	Number of samples
Asphalt shingle	75
Concrete tile	25
Clay tile	36
Metal roofing	5
Single-ply membrane	30
Modified bitumen cap sheet	14
Field-applied coating	5
Total	190

Warning: All graphics below are low resolution. Please be sure to use the supplied high resolution PDFs for typesetting.

Figure 1. Schematic of our approach for computing the mean albedo of individual roofs from the aerial imagery.

Figure 2. Examples of the 1 m resolution remotely sensed imagery for a portion of San Jose, California, showing reflectance in four narrow bands: (a) blue (420 – 492 nm), (b) green (533 – 587 nm), (c) red (604 – 664 nm), and (d) near-IR (833 – 920 nm).

Figure 3. Example building outlines. Outlines provided by the City of San Jose are shown in (a) and (b). Manually traced outlines in Sacramento are in (c). In (a) and (c) the underlying imagery is an RGB composite of the aerial imagery described in this paper. Panel b uses higher-resolution (but not radiometrically calibrated) background imagery from the United States Geological Survey) to better resolve fine features.

A. Metal roof

B. White membrane

C. Cap sheet

Figure 4. Solar spectral reflectances of three roofing products: (A) metal (zincalume with clear resin), (B) white membrane, and (C) granule-surfaced modified bitumen cap sheet. Also shown is the solar spectral global horizontal irradiance at Earth's surface (black line) assuming clear sky with the sun at zenith, referred to as Air Mass 1 Global Horizontal (AM1GH). Narrowband spectral ranges (blue, green, red, near-IR) for the airborne digital sensor (ADS80/SH82) used to collect the imagery are shaded.

a.

b.

Figure 5. Assessment of the empirical model for relating broadband reflectances to narrowband reflectances. All values are computed using solar spectral reflectance measurements of the 190 roof samples (Table 2). In (a) visible reflectance $V(b_k, g_k, r_k)$ computed using Eq. (7) is compared to V_k calculated from Eq. (1). The corresponding histogram of residuals is shown in (b). χ is the root mean square of the residuals. In (c), solar reflectance $S(b_k, g_k, r_k, i_k)$ computed using Eq. (8) is compared to S_k calculated from Eq. (1); the corresponding histogram of residuals is shown in (d).

c.

d.

Figure 5 (continued)

Figure 6. Comparison of measured albedos (ground truths) to (uncalibrated) remotely sensed albedos. The equations shown were applied to the uncalibrated remotely sensed albedos $S(b_k, g_k, r_k, i_k)$ to compute calibrated values S' using Eq. (3). Coefficients of determination (R^2) for each power law fit are shown. Estimated errors for the calibrated remotely sensed albedos are in Table 3.

Figure 7. A portion of San Jose showing the mean (calibrated) remotely sensed albedo for each rooftop. Albedos correspond to estimated bihemispherical solar reflectance.