Abstract: Urban surface albedo is important for investigating urban surface–atmosphere radiative heat exchanges. For modeling surface energy balance (SEB) at local and neighborhood scales, ground or unmanned aerial vehicle (UAV)-based multispectral remote sensing (RS) can be used to obtain high-spatial-resolution multispectral information for both horizontal and vertical urban surfaces. The existing narrow-to-broadband (NTB) conversion models, developed for satellite/high-altitude observation and large homogeneous rural/vegetated/snow zones, may not be suitable for downscaling to the local and neighborhood scales or the urban complex texture. We developed three NTB models following published methodologies for three common UAV-based multispectral cameras according to Sample_D, a sample group of extensive spectral albedos of artificial urban surfaces, and evaluated their performance and sensitivities to solar conditions and surface material class. The proposed models were validated with independent samples (Sample_V). A model considering albedo physics was improved by multiplying different variables with respect to the camera (termed as “Model_phy_reg”), which initially proved to be the most accurate with a root mean square error of up to 0.02 for Sample_D and approximately 0.029 for Sample_V, meeting the required accuracy of total shortwave albedo for SEB modeling. The accuracy of Model_phy_reg was not much prone to the solar conditions.

Keywords: albedo; narrow-to-broadband conversion; multispectral camera; urban surface; construction material

1. Introduction

Albedo quantifies the capacity of an urban surface to reflect solar radiation, which is a driving factor of the surface energy balance (SEB) [1,2]. Large natural surfaces in urban areas have been replaced by construction materials, such as asphalt for roads and concrete for buildings, increasing air and surface temperatures and resulting in the urban heat island (UHI) phenomenon [3]. Albedos are involved in radiative heat exchanges and tie the urban climate to the surface cover [4,5], and their modification (e.g., cool roof) as a strategy to mitigate UHI effect has been widely studied [6–9].

Obtaining the urban surface albedo is crucial to model SEB, to understand UHI formation/pattern and to predict and quantify the actual performance of the albedo modification strategy. Albedo and reflectance can be obtained in situ using pyranometers and spectroradiometers [10–12]. Satellite remote sensing (RS) techniques have been widely applied for estimating land surface albedo [13–15]. However, while studying the urban microclimate at local and neighborhood scales, in situ “point” measurements and satellite RS have their limitations. The former is time-consuming, labor-intensive, provides...
limited points of each surface, and cannot easily access certain surfaces (e.g., roofs), whereas the spatial resolution of the latter is not sufficient (e.g., even with Sentinel 2, which has a 10 m spatial resolution [16,17], small structures show mixed pixels [18]). A few studies have contributed in filling a gap between ground measurements and satellite RS by airborne (e.g., aircraft and airships) RS, such as the study on the high-spatial- and spectral-resolution hyperspectral airborne data to estimate broadband albedo [19]. However, airborne RS requires high labor and financial cost [20], and there is a lack of vertical surface data [21]. Rapid development of unmanned aerial vehicles (UAVs) equipped with spectral cameras has enabled obtaining both horizontal and vertical urban surface albedo with fine spatial resolution to further bridge the gap between in situ and spaceborne/airborne observations. Few studies recently applied UAV-based hyperspectral RS to retrieve land surface albedo [22]. Satellite and airborne hyperspectral RSs with sophisticated sensors such as Airborne Hyperspectral Scanner (AHS) are applied in a broad range of fields such as agriculture and forestry [23], but the UAV-hyperspectral RS is in its early stages and is yet to become widespread due to its high cost (> 100,000 USD) and operational issues (limited flight duration due to the heavy weight and battery performance, and geometric correction) [24]. Although consumer-grade digital cameras are inexpensive and easy-to-operate, they are inadequate for accurately estimating the total shortwave (SW) albedo due to the lack of near-infrared (NIR) bands [18,25]. Compared to the UAV-hyperspectral- and consumer-grade digital camera, a multispectral camera is relatively inexpensive, robust, and widely used, thus achieving an applicability–cost balance [25]. Multispectral images provide the surface reflectance at limited bands with narrow-wavelength bandwidths in each pixel and depend on the spectral responses of camera channels (e.g., 5 bands for a RedEdge camera). However, monitoring surface energy budget and modeling their efforts require broadband albedos [26], such as the total SW albedo that is crucial to SEB modeling [27,28]. Therefore, estimating broadband albedo from narrowband spectral reflectance at the sensor viewing angle is critical, and requires three processes in general [18,29,30]: (1) radiometric calibration converting digital numbers to surface directional reflectance, accounting for atmospheric and solar conditions as well as sensor noise (response of the photo-sensitive items is included), (2) surface bidirectional reflectance distribution function (BRDF) modeling to convert surface directional albedo at the viewing angle into hemispheric albedo, and (3) narrow-to-broadband (NTB) conversion of albedo. Though it is ideal to conduct the BRDF modeling [31,32], it requires measurements at multiple illuminations and multi-angular observations, involving elaborate preparation and post-processing [32–34]. Therefore, it is unnecessary to adopt the BRDF modeling for heterogeneous surfaces [17,18], and it is common to assume the target surface as Lambertian and that the reflectance is near isotropic from different viewing and solar/illumination angles [18,35]. In this paper, we focused on the third process, NTB conversion, following the same assumptions as those for isotropic reflection.

The models for NTB conversions for spaceborne sensors have been widely proposed and improved over the years, such as the Advanced Very High Resolution Radiometer (AVHRR) [14,36–38], Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) [14], Landsat-7 Enhanced Thematic Mapper Plus (ETM+) [14], Moderate Resolution Imaging Spectroradiometer (MODIS) [14,31,39,40], Sentinel-2A [17,41], and Visible Infrared Imaging Radiometer Suite (VIIRS) [39,42,43]. Liang explored the easy-to-use NTB model for universal application over different surface cover types for common sensors by regressing the conversion coefficients based on extensive radiative transfer simulations and spectral reflectance database [14,29]. A further conversion, proposed by Tasumi et al. [40], used a physics-based approach to integrate narrowband reflectance viewed at nadir with weighting coefficients representing the solar radiation fraction within each sensor spectral band. Recently, a few studies retrieved broadband albedo from Sentinel-2 Multispectral Instrument (MSI) bands with a 10 m pixel size using the same coefficients as those for ETM+ proposed by Liang [14], whereas Li et al. [41] calculated the NTB coefficients for Sentinel-2 MSI based on Liang [14]’s regression strategy. Bonafoni et al. [17] compared the model using Li et al. [41]’s coefficients and the one based on Tasumi et al [40]’s physics-based strategy.
UAV-based RS has been studied only recently as an alternative to estimate albedo [18,35]. Cao et al. [18] directly adopted Landsat 8 NTB coefficients, as provided by Wang et al. [31], using a consumer-grade digital camera on board a UAV. Appropriate NTB conversion models are needed for UAV-based multispectral cameras as directly adopting existing NTB coefficients would be difficult due to the different bandwidths and central wavelengths of the sensor channels (Figure 1), and the existing models developed for satellite/high-altitude observation and large homogeneous rural/vegetated/snow zones may not be suitable for local and neighborhood scales and to the urban complex texture. Meanwhile, an advantage of UAV-based observation is the capture of vertical surface data, which brings more uncertainty in adopting the existing models developed solely for horizontal surfaces.

Figure 1. Spectral bands of commonly used spaceborne and UAV-based multispectral sensors/cameras.

The aim of this study was to obtain NTB conversion models for UAV/ground-based multispectral cameras and urban surfaces. Based on the measured spectral reflectances of urban surfaces and simulated at-surface solar spectral irradiances under various conditions (season, solar zenith angle, and horizontal/vertical surface), we simulated datasets of extensive spectral albedos of urban surfaces. Based on the built datasets of various at-surface solar irradiances and spectral albedos, we developed three NTB conversion models following published methodologies (Model_reg following Liang [14], Model_phy following Tasumi et al. [40], and Model_phy_reg as an improvement of Model_phy) for three common UAV-based multispectral cameras for urban surfaces, and evaluated their performance as well as the camera capacity to estimate broadband albedo. In addition, the models’ sensitivities to the solar conditions (season, solar zenith angle, and horizontal/vertical surface) and the surface material class were analyzed. These models were also validated using independent sample surfaces covered by different construction materials.

2. Materials and Methods

2.1. Study Cameras and Urban Surface Materials

As shown in the lower part of Figure 1, UAV-based multispectral sensors can be categorized based on their bandwidths [25]: one with narrow spectrum range, such as the Mini-MCA6 (Tetracam Inc., Chatsworth, CA, USA) with narrow bandwidths (bands 1–5 are 10 nm, band 6 is 20 nm), and the other with a wider spectrum range, such as the ADC-Micro (Tetracam Inc., Chatsworth, CA, USA) with a minimum bandwidth of 60 nm. The Mini-MCA6 has twice the number of bands as that of ADC-Micro. Their typical characteristics are representatives of commonly used UAV-based cameras. In addition, the RedEdge (Rededge-M, MicaSense Inc., Seattle, WA, USA), which has a median band number and bandwidth between Mini-MCA6 and ADC-Micro, was also studied.
ADC-Micro, Mini-MCA6, and RedEdge were thus selected for the study. Their bands, spectral ranges, and other main parameters are shown in Table 1.

| Sensor     | Blue Band/B (nm) | Green Band/G (nm) | Red Band/R (nm) | Red-Edge Band/RE (nm) | NIR Band/NIR1 (nm) | NIR Band/NIR2 (nm) | Resolution (Pixels)/Weight (g) |
|------------|------------------|-------------------|-----------------|-----------------------|-------------------|-------------------|-------------------------------|
| ADC-Micro  | 520–600          | 630–690           | -               | 760–900               | -                 | -                 | 2018 × 1536/200               |
| Mini-MCA6  | 485–495          | 545–555           | 675–685         | 715–725               | 795–805           | 890–910           | 1280 × 1024/700               |
| RedEdge    | 465–485          | 550–570           | 663–673         | 712–722               | 820–860           | -                 | 1280 × 960/150                |

Concrete, asphalt, tile, wall coating, stone, brick, and wooden slat were selected as these are the commonly used building materials for urban surfaces in Japan [44,45].

2.2. Technical Process

The technical process is shown in Figure 2, which also provides a workflow of developing the NTB conversion formulae and the steps for estimating broadband albedo through UAV-based multispectral imagery. The crucial step is building sample groups to develop conversion formulae and validate their applicability. This requires datasets of various spectral reflectance and at-surface solar spectral irradiance, as both narrowband and broadband albedos are not the sole measures of physical properties (e.g., absolute reflectance), but also depend on the atmospheric conditions through the at-surface solar fluxes, influencing the NTB conversion’s weighting function. Therefore, we measured spectral reflectance of various urban surfaces using a spectroradiometer from a nadir position (Section 2.3.1 for details) and simulated the at-surface solar spectral irradiances under various conditions (Section 2.4.1). Based on the obtained solar irradiance and spectral reflectances, the broadband and narrowband albedos were calculated (Sections 2.4.1 and 2.4.2) and segregated in two sample groups. Sample_D, composed of 2424 samples from 101 urban surfaces and 24 at-surface solar spectral irradiances (season, solar zenith angle, and horizontal/vertical surface), was used to develop three conversion models for each camera based on the published conversion strategies. Sample_V included 23 independent urban surfaces and was used to validate the conversion models. Meanwhile, in order to validate the models’ applicability to UAV-based multispectral imagery, the narrowband and broadband albedos of Sample_V were also derived from a RedEdge camera (Sections 2.3.2 and 2.4.3) and the conversion models (developed in Section 3). The reason not solely use the multispectral data for validating the models was to avoid the possible errors/biases caused by multispectral RS images (e.g., camera (radiometric aberration and camera setting), platform (whether the camera is pointing nadir and at the target), and the environment (sky, wind, and illumination conditions) [46]). The in situ measurement, radiative transfer simulation, and related calculations are described in the following sections.
2.3. In Situ Measurement and Ground-Based Remote Sensing

2.3.1. In Situ Measurement of Spectral Reflectance

If the surface is tough without dominating three-dimensional structures and assumed to be Lambertian, the nadir-viewing reflectances are numerically equal to the spectral albedos [14,17,29,47]. The spectral reflectances of target surfaces were measured at nadir using a spectroradiometer (ASD FieldSpec4, ASD Inc., Alpharetta, GA, USA) under an artificial illumination and were adopted as spectral albedos. The ASD FieldSpec4 detects light continuously over the visible (VIS) and near-infrared (VNIR) to shortwave infrared (SWIR) wavelengths with a 25° field of view (FOV) and a spectral resolution of 3 nm at VNIR (350–1000 nm in wavelength) using a silicon detector, and 10 nm for two sets of SWIR bands, ranging from 1001–1800 nm and 1801–2500 nm, using a detector made of thermoelectric-cooled indium gallium arsenide. We conducted the measurements under an artificial illumination provided by an ASD Contact Probe (ASD Inc., Alpharetta, GA, USA) to reduce errors associated with stray light, allowing our measurements to be carried out at any time of the day.

The target surfaces comprised of 22 concrete, 22 stone, 16 tile, 14 brick, 20 surface coating, 14 asphalt, and 16 wooden slat coverings. Among them, 19 concrete, 19 stone, 13 tile, 11 brick, 15 surface coating, 11 asphalt, and 13 wooden slat surface specimens formed Sample_D as shown in Figure 3, and were measured in the central Nagoya city, Japan (Lat./Lon.: 35° 10’ 26” N/136° 54’ 28” E) in October, 2012. The other samples formed Sample_V, and were measured in a university campus in Yokohama city, Japan (Lat./Lon.: 35° 30’ 45” N/139° 29’ 04” E) during January–February, 2020. The mean spectral reflectance of the surface specimens within each material class for Sample_D was calculated as the typical spectral reflectance within each material class and is represented by black curves in Figure 3. We also measured spectral reflectance for a grey reference panel (RP, approximately 49% reflectivity, MicaSense Inc., USA) for calibrating the multispectral images.
Figure 3. Spectral reflectances of urban surface specimens and the typical spectral reflectance within a single construction material class.

Figure 3 reveals that the spectral reflectance showed similar spectral variation within a single class, mainly due to similar chemical/mineralogical constituents. For example, concrete is composed of silica, carbonates, and a few other minerals. However, its spectral radiative response is dominantly driven by siliceous and calcareous minerals. As shown in Figure 3, regardless of the higher or lower reflectance in general, all SW spectra of the concrete class revealed an increase in reflectance up to 600 nm and a strong absorption at around 1950 nm. The latter indicates that $\text{H}_2\text{O}$ is related to the absorption of the gypsum component, corresponding to Kotthaus et al.’s finding [48]. Asphalt is often used for road surfaces and comprises various natural bitumen composed of solid or semi-solid hydrocarbon mixtures, causing an increasing reflectance with longer wavelengths [49] (Figure 3). As shown in Figure 3, most tiles, which usually consist of clay-based ceramics, showed an increasing reflectance up to around 600/800 nm and absorption at around 1950 nm. As compared to the spectral reflectance of a single material class [48], most construction material classes showed similar spectral variation. However, certain spectral reflectance of the brick and tile in [48] showed different spectral features. These exceptions, mainly composed of concrete/cement, which exhibited similar spectral features as those of concrete. Thus, their spectral variation could additionally be captured by our NTB conversion models.

2.3.2. Ground-Based Multispectral Remote Sensing

Although we aimed to estimate broadband albedo using the UAV-base multispectral camera, as a first step, we used a handheld RedEdge camera and observed from the ground-level during the solar noon (11:00–15:00) of February 12–15, 2020 in the campus at Yokohama City, Japan. The experience of ground-based multispectral RS and developed workflow formed the foundation for the next step, the UAV-mounted observation. The camera was placed around 1 m just above the horizontal surface or far from the vertical surface, with the same orientation with respect to the sun as the target surface. In the meantime, the multispectral images of the RP were taken. Notably, RP was placed at the same position and orientation as the target surface to guarantee similar solar and observation angles and the illumination received as the target surface.
2.4. Calculation of Broadband and Narrowband Albedos

2.4.1. Calculation of Total Shortwave Albedo (Broadband Albedos)

The total SW wavelength range was selected as 350–2500 nm. This covered almost all the solar radiation at surface as the downward fluxes beyond this range were negligible. Based on the spectral albedo, the total SW albedos ($\alpha_{SW}$) can be calculated by integrating the spectral reflectance ($\rho$) and multiplying the spectral irradiance of solar radiation ($R_s$) with the wavelength ($\lambda$) within the SW range.

$$\alpha_{SW} = \int_{350}^{2500} \rho(\lambda_i) R_s(\lambda_i) \, d\lambda / \int_{350}^{2500} R_s(\lambda_i) \, d\lambda$$ (1)

The Simple Model of Atmospheric Radiative Transfer of Sunshine software (SMARTS 2.9.5, National Renewable Energy Laboratory, Golden, CO, USA) offers fast and accurate predictions on how the distribution of solar power for each wavelength of light traveling from the sun is modified by atmospheric changes [50,51]. Users can construct text files with dozens of lines of text and numbers to specify input atmospheric conditions and to output simulated cloud-free spectral irradiances, including direct beam, hemispherical diffuse, circumsolar, and total on a tilted/horizontal receiver surface. The SMARTS model has been widely applied over a large number of scientific and technologic disciplines [52], and its performance was validated with typical differences within 2% when compared to the sophisticated models (MODTRAN, SBDART, COART, and LibRadtran), and mostly within 5% as the instrumental uncertainty when compared to spectroradiometric measurements [53,54]. Therefore, we used the SMARTS model to simulate cloud-free solar spectral irradiance at the target surfaces. The simulation for Sample_D was conducted by keeping the study site location and suggested UAV-based RS conditions (clear sky and near-solar noon (late noon for vertical surfaces)) fixed, while the season, solar zenith angle (SZA), and horizontal/vertical urban surface were varied (Table 2). As the rough surfaces such as soils showed almost no changing values of albedo at SZAs lower than 75° [55], UAV-based RS is suggested in late solar noon for the vertical surface rather than the noon to avoid the high SZAs (> 75°) with respect to vertical surfaces, which would not bring much error caused by the Lambertian assumption. The study site is located at 35° 30’ 45” N and 139° 29’ 04” E, where the SZA near summer noon (11:00–14:00) ranges between 0°–30° and is close to 40° for late noon (14:00–15:00). The winter near-noon (11:00–14:00) SZA is approximately 40°–70°, and 70°–80° around 15:00. The reference atmosphere for simulating was either mid-latitude winter or summer standard atmosphere with corresponding conditions (Table 2).

Table 2. The conditions used while simulating solar spectral irradiances.

| Case   | Horizontal/Vertical Surface | Season | Solar Zenith Angle | Surface Azimuth (°) | Case   | Horizontal/Vertical Surface | Season | Solar Zenith Angle | Surface Azimuth (°) |
|--------|-----------------------------|--------|--------------------|---------------------|--------|-----------------------------|--------|--------------------|---------------------|
| Rs_1   | Horizontal                  | Winter | 40°                | -                   | Rs_13  | Vertical                    | Winter | 70°                | 50°                 |
| Rs_2   | Horizontal                  | Winter | 50°                | -                   | Rs_14  | Vertical                    | Winter | 70°                | 140°                |
| Rs_3   | Horizontal                  | Winter | 70°                | -                   | Rs_15  | Vertical                    | Winter | 70°                | 230°                |
| Rs_4   | Horizontal                  | Winter | 80°                | -                   | Rs_16  | Vertical                    | Winter | 70°                | 320°                |
| Rs_5   | Horizontal                  | Summer | 0°                 | -                   | Rs_17  | Vertical                    | Summer | 30°                | 50°                 |
| Rs_6   | Horizontal                  | Summer | 10°                | -                   | Rs_18  | Vertical                    | Summer | 30°                | 140°                |
| Rs_7   | Horizontal                  | Summer | 20°                | -                   | Rs_19  | Vertical                    | Summer | 30°                | 230°                |
| Rs_8   | Horizontal                  | Summer | 30°                | -                   | Rs_20  | Vertical                    | Summer | 30°                | 320°                |
| Rs_9   | Vertical                    | Winter | 50°                | 50°                 | Rs_21  | Vertical                    | Summer | 40°                | 50°                 |
| Rs_10  | Vertical                    | Winter | 50°                | 140°                | Rs_22  | Vertical                    | Summer | 40°                | 140°                |
| Rs_11  | Vertical                    | Winter | 50°                | 230°                | Rs_23  | Vertical                    | Summer | 40°                | 230°                |
| Rs_12  | Vertical                    | Winter | 50°                | 320°                | Rs_24  | Vertical                    | Summer | 40°                | 320°                |

The simulation input for Sample_V accounted for the ground-based RS dates (February 12–15, 2020) and duration (11:00–14:00), and the mid-latitude winter standard atmosphere was selected as the
reference atmosphere, the SZA was set at 50°, and the surface tilt angle and azimuth were set according to the actual conditions (Table 3).

### Table 3. Samples used for validation.

| Sample  | Horizontal/Vertical Surface | Surface Azimuth | Sample  | Horizontal/Vertical Surface | Surface Azimuth |
|---------|-----------------------------|-----------------|---------|-----------------------------|-----------------|
| Concrete_1 | Vertical                     | 50°             | coating_1 | Horizontal                 | -               |
| Concrete_2 | Horizontal                   | -               | coating_2 | Horizontal                 | -               |
| Concrete_3 | Vertical                     | 230°            | coating_3 | Vertical                   | 140°           |
| Stone_2  | Horizontal                   | -               | coating_4 | Vertical                   | 140°           |
| Stone_3  | Horizontal                   | -               | coating_5 | Vertical                   | 320°           |
| Stone_1  | Horizontal                   | -               | Asphalt_1 | Horizontal                 | -               |
| Stone_2  | Horizontal                   | -               | Asphalt_3 | Horizontal                 | -               |
| Tile_1   | Vertical                     | 140°            | Asphalt_2 | Horizontal                 | -               |
| Tile_2   | Vertical                     | 140°            | Asphalt_3 | Horizontal                 | -               |
| Tile_3   | Vertical                     | 140°            | Woodenslabs_1 | Horizontal             | -               |
| Brick_1  | Horizontal                   | -               | Woodenslabs_2 | Horizontal             | -               |
| Brick_2  | Horizontal                   | -               | Woodenslabs_3 | Horizontal             | -               |
| Brick_3  | Horizontal                   | -               | -               | -                          | -               |

2.4.2. Calculation of Narrowband Albedo Based on Spectral Reflectance

The simulated solar irradiances and the measured spectral reflectances were normalized to have a 1 nm spectral resolution. The Nth narrowband albedo can be calculated by integrating spectral reflectances and solar spectral irradiance within the band spectral range corresponding to the ones captured by the study sensors, as shown in Equation (2).

$$
\alpha_N = \frac{\int_{a_N}^{b_N} \rho(\lambda_i) R(\lambda_i) \, d\lambda}{\int_{a_N}^{b_N} R(\lambda_i) \, d\lambda}
$$

where $\alpha_N$ is narrowband albedo of the target surface, $\rho(\lambda_i)$ and $R(\lambda_i)$ are the surface spectral reflectance and at-surface solar spectral irradiance at wavelength $\lambda_i$ (nm), respectively, and $a_N$ and $b_N$ are the lower- and upper-wavelength limits, respectively, corresponding to band N. For example, the RedEdge camera can capture narrowband albedos of five bands; band wavelengths are shown in Table 1 as 465–485 (Blue), 550–570 (Green), 663–673 (Red), 712–722 (RedEdge), and 820–860 (NIR). These band wavelength limits were input into Equation (2) to calculate the narrowband albedos.

2.4.3. Calibration of Multispectral Images to Convert Raw Pixel Values to Albedo

RedEdge images were processed in Python3, OpenCV, numpy, matplotlib, and the standalone exiftool, and manipulated using Python wrapper, following the RedEdge user manual [56]. Optical and natural vignette, exposure, and row correction were conducted to convert raw pixel values to radiances. The calibration formula for calculating the spectral radiance (L, W/m²/sr/nm) for the ith band is described in Equation (3). The pixel and black level value were normalized by dividing their raw digital number by $2^N$, where N is the number of image bits (e.g., $2^N = 65536$ for 16-bit images).

$$
L_i(x, y) = V_i(x, y) \frac{a_{1,i}}{g_i} \frac{P_i(x, y) - P_{BL,i}}{t_e,i + a_{2,i}y - a_{3,i}t_e,iy}
$$

where $V_i(x, y)$ is the vignette polynomial function for pixel location $(x, y)$, $a_{1,i}$, $a_{2,i}$, and $a_{3,i}$ are radiometric calibration coefficients, $P_i(x, y)$ is the normalized raw pixel value for pixel location $(x, y)$, $P_{BL,i}$ is the normalized dark level value, $g_i$ is the sensor gain, $t_e,i$ is the image exposure time [s], and x and y are the pixel column and row number, respectively. The $V_i(x, y)$ can be described as:

$$
V(x, y) = 1 / (1 + k_0 r_i + k_1 r_i^2 + k_2 r_i^3 + k_3 r_i^4 + k_4 r_i^5 + k_5 r_i^6)
$$
where \( k_{0,i} \) through \( k_{5,i} \) represent polynomial correction coefficients and \( r_i \) is the distance of the pixel \((x, y)\) to the vignette centers, estimated using:

\[
r_i = \sqrt{(x - c_{x,i})^2 + (y - c_{y,i})^2}
\]

(5)

where \( c_{x,i} \) and \( c_{y,i} \) are the coordinates of vignette center for the \( i \)th band. The \( L_i(x, y) \) can be calculated using Equations (3)–(5).

In contrast to the absolute reflectance retrieval given by RedEdge user manual, we conducted a radiance-to-directional reflectance conversion by calculating its calibration factor using the multispectral image of RP (Section 2.3.2) with known spectral reflectances (Section 2.3.1). After being converted into radiance using Equations (3)–(5), the RP directional reflectance in each band was calculated following Equation (2) with band spectral ranges as input and simulated close-to-actual solar irradiance on RP (Section 2.4.1). The radiance-to-directional reflectance factor for the band \( i \) (\( F_i \)) is estimated as:

\[
F_i = \rho_{Oi} / \text{avg}\left(L_{\alpha,i}(x_1 - x_2, y_1 - y_2)\right)
\]

(6)

where \( \rho_{Oi} \) is the directional reflectance and \( \text{avg}\left(L_{\alpha,i}(x_1 - x_2, y_1 - y_2)\right) \) is the average radiance of the pixels inside the RP, \((x_1 - x_2, y_1 - y_2)\), for band \( i \).

Multiplying the factor \( F_i \) converts all radiance values into the surface directional reflectance including the calibration of the spectral response of the camera channel for the \( i \)th band. As the selected urban surfaces are quite rough, homogeneous, without dominating 3D structures, and the multispectral RS was conducted near midday (late midday for vertical surfaces) ensuring a relatively large solar elevation angle, we assumed them as approximately Lambertian surfaces. Their directional reflectances were thus numerically equal to the surface albedos. This process can be applied to each of the five bands individually.

2.5. Variable Selection for the Sensitivity Analysis

Broadband albedo also depends on the solar conditions through downward fluxes influencing the weighting function of the NTB conversion. Gul et al. showed that the variation in albedo with changing cloud conditions (overcast, partly cloudy, and clear) for sand, cement slabs, and white tiles was less than 0.05 [57]. Liang et al. concluded that the broadband albedos are relatively stable unless the SZA is extremely large [14], and the asphalt surface albedo is not prone to solar elevation [29]. Considering the suggested near-solar noon time and clear skies for UAV-based RS, we did not investigate the developed conversion models’ sensitivity to overcast skies, but analyzed their dependency to SZAs, the ranges for which were calculated for solar noon (late noon for vertical surface) in winter or summer. Accounting for the fine spatial resolution and accessibility to measure the vertical surface of UAV-based RS, the models’ sensitivity to the construction material class and its applicability to the vertical surface albedo were also investigated. Therefore, season, SZA, horizontal/vertical surface, and construction material class were selected to analyze model sensitivity.

3. Model Development

3.1. Conversion Model

The NTB conversion models for Sample_D followed published algorithms (Liang’s [14] and Tasumi et al.’s [40]) to estimate the total SW albedo for ADC-Micro, Mini-MCA6, and RedEdge.

3.1.1. Model by Applying Regression-Based Strategy

Using spectral reflectance database and radiative transfer simulations, Liang [14] investigated the coefficients for NTB conversion for typical spaceborne sensors using regressions derived from extensive sampling under various atmospheric and surface covers. The conversion models following
Liang’s strategy were established by the linear regression using the Least Squares Method named “Model_reg”, and are shown in Equations (7)–(9).

- **ADC-Micro:**
  \[
  \alpha_{\text{Mic,reg}} = 0.7028G - 0.4155R + 0.6222NIR + 0.009
  \]  
  (7)

- **Mini-MCA6:**
  \[
  \alpha_{\text{MCA6,reg}} = 0.3668B - 0.0449G + 0.2183R + 0.2105RE - 0.5914NIR1 + 0.7708NIR2 + 0.0075
  \]  
  (8)

- **RedEdge:**
  \[
  \alpha_{\text{RedEdge}} = 0.3973B - 0.0102G + 0.0454R - 0.1017RE + 0.6116NIR + 0.0075
  \]  
  (9)

3.1.2. Model by Applying Physics-Based Strategy

The other easy-to-use conversion models follow Tasumi et al.’s strategy [40] used for Landsat and MODIS data under cloud- and snow-free, low-haze conditions, and sensor viewing angles not more than 20°. For each study camera, the broadband albedo of target surface was estimated by integrating narrowband albedos across the SW spectrum as below:

\[
\alpha = \sum \alpha_N w_N
\]  
(10)

where \( \alpha_N \) is the albedo for Nth band and \( w_N \) is the weighting coefficient, estimated as:

\[
w_N = \int_{b_N}^{a_N} R(\lambda_i) d\lambda / \int_{350}^{2500} R(\lambda_i) d\lambda
\]  
(11)

where \( R(\lambda_i) \) is the at-surface solar irradiance at wavelength \( \lambda_i \) (nm) and \( a_N \) and \( b_N \) denote the waveband range of band N. The conversion models following Tasumi et al. [40] are named "Model_phy", assuming that reflectances in the missing wavelength regions are estimated by linear interpolation of adjacent bands’ albedos. The weighting coefficients listed in Table 4 are based on the simulated 24 at-surface solar irradiances (Table 2) and spectral ranges of camera channels (Table 1).

| Sensor | ADC-Micro | Mini-MCA6 | RedEdge |
|--------|-----------|-----------|---------|
| Variable | 0.9141 | 0.9193 | 0.9282 |
| Channel | | | |
| Rs_1   | 0.3632 | 0.1462 | 0.4950 |
| Rs_2   | 0.3571 | 0.1472 | 0.4999 |
| Rs_3   | 0.3362 | 0.1477 | 0.5180 |
| Rs_4   | 0.3225 | 0.1438 | 0.5372 |
| Rs_5   | 0.3850 | 0.1515 | 0.4682 |
| Rs_6   | 0.3843 | 0.1515 | 0.4689 |
| Rs_7   | 0.3839 | 0.1517 | 0.4690 |
| Rs_8   | 0.3800 | 0.1522 | 0.4694 |
| Rs_9   | 0.6459 | 0.1233 | 0.2345 |
| Rs_10  | 0.3516 | 0.1503 | 0.5024 |
| Rs_11  | 0.3345 | 0.1513 | 0.5186 |
| Rs_12  | 0.6328 | 0.1283 | 0.2427 |
| Rs_13  | 0.6124 | 0.1301 | 0.2612 |
| Rs_14  | 0.2918 | 0.1541 | 0.5581 |
| Rs_15  | 0.2764 | 0.1544 | 0.5732 |
| Rs_16  | 0.5907 | 0.1347 | 0.2695 |
| Rs_17  | 0.6675 | 0.1247 | 0.2316 |
| Rs_18  | 0.6504 | 0.1321 | 0.2216 |
| Rs_19  | 0.3977 | 0.1523 | 0.4546 |

Table 4. Physical weighting coefficients for sensors and solar irradiance (Rs_i).
Table 4. Cont.

| Sensor            | ADC-Micro | Mini-MCA6 | RedEdge |
|-------------------|-----------|-----------|---------|
| Variable *        | 0.9141    | 0.9193    | 0.9282  |

| Rs_20  | 0.5086 | 0.1439 | 0.3519 | 0.3422 | 0.1641 | 0.1254 | 0.0622 | 0.0770 | 0.2422 | 0.3362 | 0.1750 | 0.1107 | 0.0811 | 0.3085 |
| Rs_21  | 0.6709 | 0.1232 | 0.2097 | 0.5006 | 0.1664 | 0.1127 | 0.0489 | 0.0569 | 0.1270 | 0.4918 | 0.1812 | 0.0982 | 0.0638 | 0.1762 |
| Rs_22  | 0.6478 | 0.1331 | 0.2233 | 0.4685 | 0.1747 | 0.1217 | 0.0527 | 0.0612 | 0.1343 | 0.4602 | 0.1893 | 0.1063 | 0.0687 | 0.1872 |
| Rs_23  | 0.3800 | 0.1544 | 0.4703 | 0.2261 | 0.1542 | 0.1289 | 0.0712 | 0.0921 | 0.3407 | 0.2220 | 0.1617 | 0.1149 | 0.0928 | 0.4199 |
| Rs_24  | 0.4766 | 0.1472 | 0.3807 | 0.3128 | 0.1622 | 0.1269 | 0.0646 | 0.0811 | 0.2656 | 0.3072 | 0.1723 | 0.1122 | 0.0843 | 0.3354 |

Variable *: the value used to multiply the weighting coefficients for each camera in Model_phy_reg.

3.1.3. Conversion Formulae by Improving Physically Based Methodology

After verifying the accuracy of Model_phy, we found that the estimated results were linearly correlated with the measured results, though the difference increased as the albedos increased (see Section 3.2 and Figure 4). To improve accuracy, we multiplied the weighting coefficients for each camera with a value of approximately 0.9 (second row of Table 4), calculated by the linear regressions without intercepts, and developed an improved model named “Model_phy_reg”.

3.2. Performance Evaluation

We used the SW albedos calculated by the measured spectral reflectance and simulated solar irradiance (Section 2.4.1) to evaluate the models developed (Figure 4) for the three cameras, with the measures of R-square (R^2), Root Mean Square Error (RMSE), Residual Standard Error (RSE), and Mean Bias Error (MBE) (Table 5).

Table 5. Measures of R^2, RMSE, RSE, and MBE.

|                      | R^2    | RMSE  | RSE   | MBE       |
|----------------------|--------|-------|-------|-----------|
| Regression-Based     |        |       |       |           |
| (Model_reg) ADC-Micro| 0.9796 | 0.0227| 0.0227| 7.42691 × 10^{-16} |
| Mini-MCA6            | 0.9827 | 0.0209| 0.0209| 4.29695 × 10^{-16} |
| RedEdge              | 0.9805 | 0.0222| 0.0222| 5.70368 × 10^{-16} |
| Physically Based     |        |       |       |           |
| (Model_phy) ADC-Micro| 0.9618 | 0.0330| 0.0330| 0.0189    |
| Mini-MCA6            | 0.9673 | 0.0287| 0.0287| 0.0182    |
| RedEdge              | 0.9700 | 0.0275| 0.0275| 0.0152    |
| Improved Physically  |        |       |       |           |
| Based (Model_phy_reg)|       |       |       |           |
| ADC-Micro            | 0.9835 | 0.0204| 0.0204| −0.0022   |
| Mini-MCA6            | 0.9907 | 0.0153| 0.0153| −0.0016   |
| RedEdge              | 0.9881 | 0.0173| 0.0173| −0.0022   |

As shown in Figure 4, the three models performed well, with a generally low RMSE of up to 0.033. Model_phy_reg was the most accurate among the three models, as shown in the third row of Figure 4, with a highest R^2 (0.98–0.99) and a lowest RMSE of approximately 0.02. This was closely followed by Model_reg with RMSE values that were 0.002–0.005 higher. Model_phy had the lowest accuracy among the three models, with an RMSE approximately 0.01 higher and R^2 0.01–0.02 lower. RSE is a variant of the RMSE adjusted for the number of predictors in the model. Its difference from RMSE was negligible as shown in Table 5, due to the large number of surface spectral albedos (2424) used for developing models and small number of predictors (narrow bands).

The Mini-MCA6 camera performed the best with Model_reg and Model_phy_reg, whereas the RedEdge camera performed the best with Model_phy. When applying the best algorithm (Model_phy_reg), Mini-MCA6 showed the highest R^2 of approximately 0.99 and the lowest RMSE of approximately 0.015, which was closely followed by RedEdge with an RMSE only 0.002 higher. The ADC-Micro showed the lowest performance with an RMSE of approximately 0.02.
4. Result

4.1. Sensitivity Analysis

4.1.1. Sensitivity to the Season and SZA

The RMSEs of the three model-based albedos with respect to the seasons and SZAs are shown in Figure 5. Most models performed slightly better with summer solar irradiances (first column, Figure 5), except for Model Phy used for ADC-Micro, which had the poorest performance indicated by a higher RMSE. Regarding the summer SZAs (first row, Figure 5), the performance of Model Phy and Model Phy_reg were similar, whereas Model_reg performed slightly better with the 20° SZA. As the winter SZAs increased from 40° to 70° (second row, Figure 5), the accuracy of Model_reg and
Model_phy_reg reduced marginally, whereas that of Model_phy improved, as shown by the difference in RMSE of up to 0.005.

Figure 5. RMSEs of the three model-based estimated total SW albedos with respect to the season and SZA.

4.1.2. Sensitivity to the Horizontal/Vertical Surface

The sensitivity of the NTB models to the vertical/horizontal surface and azimuth (if vertical) was evaluated using RMSE, and the results are shown in Figure 6.

Figure 6. RMSEs of the three model-based estimated albedos with respect to the axial and orientation of target surface.

As shown in the first two columns (from left) in Figure 6, most models showed higher accuracies when applied to the horizontal surface than the vertical surface: Model_phy performed significantly better with an RMSE value that was 0.006–0.01 lower, the RMSE value of Model_reg was 0.0025–0.0037 lower, and Model_phy_reg performed slightly better with RMSE value lower by 0.0017 and 0.0012 for ADC-Micro and Mini-MCA6, respectively, except for RedEdge which performed marginally lower.

In terms of the vertical surface azimuth, as shown in the last four columns of Figure 6, Model_phy demonstrated the best and worst performance with 230°- and 50°- azimuth surfaces, respectively, where the largest RMSE gap ranged between 0.009–0.014. Model_reg and Model_phy_reg performed the best and worst with the 320°- and 50°- azimuth vertical surface, respectively. The difference in
RMSE for Model_reg was 0.005–0.006. As compared to the other two models, Model_phy_reg was less sensitive to the various surface azimuths, and the largest RMSE difference was between 0.002–0.0029.

4.1.3. Sensitivity to the Class of Materials

Considering the difference in albedo among construction materials (e.g., overall low albedo of asphalt), we used the RMSE percentage of the estimated SW albedos to better evaluate the models’ dependencies on the material classes. The results, as shown in Figure 7, showed that the RMSE percentages of models applied to the urban surfaces were almost less than 15%, except for Model_phy and Model_reg applied to concrete and asphalt, respectively.

![Figure 7. RMSE percentages of the three model-based estimated albedos with respect to the surface material class.](image)

Regarding Model_reg, the best material class as the application target is the coating, whereas the worst and close-to-worst classes were asphalt and wooden slats, respectively, where the largest difference in RMSE percentage was approximately 11%. Model_phy’s best application target was the wooden slat, whereas the worst was the coating for Mini-MCA6 and RedEdge, and concrete for ADC-Micro, where the difference in RMSE percentage was up to 8%. Model_phy_reg’s application on most construction materials showed an RMSE percentage less than 11%, except for asphalt and wooden slat. Their best and worst applications were stone and wooden slat, respectively, where the RMSE percentage difference was up to 9%.

The worst application targets of Model_reg and Model_phy_reg were asphalt and wooden slat (Figure 7). Their capacity to capture spectral variations of different surface materials can be improved by developing custom models for each cover type, such as categorizing land cover into snow, soil, and vegetation for spaceborne RS [38,58]. The weighting coefficients of Model_phy remained unchanged unless the at-surface solar irradiance varied. We thus customized Model_reg and Model_phy_reg individually for the asphalt and wooden slat samples, as shown in Equations (12)–(17), in order to explore the potential for improving NTB conversion while considering different surface materials.

- Custom Model_reg for asphalt:

\[
\alpha_{\text{Mic}_\text{reg}} = 0.5011G - 0.6705R + 1.0308\text{NIR} + 0.0023 \tag{12}
\]

\[
\alpha_{\text{MCA6}_\text{reg}} = 0.3276B - 0.0196G + 0.2205R - 0.2433\text{RE} - 0.1853\text{NIR}_1 + 0.8345\text{NIR}_2 + 0.0004 \tag{13}
\]

\[
\alpha_{\text{RedE}_\text{reg}} = 0.3595B - 0.0451G - 0.8113R + 0.6996\text{RE} + 0.6437\text{NIR} + 0.0001 \tag{14}
\]

- Custom Model_reg for wooden slat:

\[
\alpha_{\text{Mic}_\text{reg}} = -0.2058G + 0.5498R + 0.5912\text{NIR} + 0.0075 \tag{15}
\]

\[
\alpha_{\text{MCA6}_\text{reg}} = 1.0432B - 1.0292G - 0.0135R + 2.9212\text{RE} - 3.8306\text{NIR}_1 + 1.8782\text{NIR}_2 + 0.01618 \tag{16}
\]
\[ \alpha_{\text{RedE\_reg}} = -0.8996B + 3.8407G + 0.2938R - 4.6087RE + 2.4312\text{NIR} + 0.007 \] (17)

The general and customized regression-based weighting coefficients for sensors as shown in Equations (7)–(9), Equations (12)–(17) were also summarized in Table 6.

**Table 6.** General and customized regression-based weighting coefficients.

| Sensor         | ADC-Micro | RedEdge | Sensor         | Mini-MCA6 | Mini-MCA6 |
|----------------|-----------|---------|----------------|-----------|-----------|
| \[ \text{G} \] | \[ \text{R} \] | \[ \text{NIR} \] | \[ \text{Constant} \] | \[ \text{B} \] | \[ \text{G} \] | \[ \text{R} \] | \[ \text{RE} \] | \[ \text{NIR} \] | \[ \text{Constant} \] |
| General        | 0.7028    | -0.4155 | 0.6222         | 0.009     | 0.3973    | -0.0102 | 0.0454 | -0.1017 | 0.6116    | 0.0075     |
| Asphalt        | 0.5011    | -0.6705 | 1.0308         | 0.0023    | 0.3595    | -0.0451 | -0.8113 | 0.6996    | 0.6437     | 0.0001     |
| Wooden Slat    | -0.2058   | 0.5498  | 0.5912         | 0.0075    | -0.8996   | 3.8407  | 0.2938 | -4.6087  | 2.4312     | 0.007      |
| \[ \text{G} \] | \[ \text{R} \] | \[ \text{NIR} \] | \[ \text{Constant} \] | \[ \text{B} \] | \[ \text{G} \] | \[ \text{R} \] | \[ \text{RE} \] | \[ \text{NIR} \] | \[ \text{Constant} \] |
| General        | 0.3668    | -0.0449 | 0.2183         | 0.2105    | -0.5914   | 0.7708  | 0.0075 |
| Asphalt        | 0.3276    | -0.0196 | 0.2205         | -0.2433   | -0.1853   | 0.8345  | 0.0004 |
| Wooden Slat    | 1.0432    | -1.0292 | -0.0135        | 2.9212    | -3.8306   | 1.8782  | 0.01618|

Instead of the general variables of 0.9141, 0.9193, and 0.9282 (second row of Table 4) to develop Model\_phy\_reg for ADC-Micro, Mini-MCA6, and RedEdge, respectively, the custom formulae applied 0.9856, 0.9714, and 1.0021, calculated by the regression for the asphalt samples, and 1.0291, 0.9979, and 1.0388 for the wooden slat samples.

A comparison of the general and custom NTB models is shown in Figure 8. It demonstrates that the customization resulted in an improvement in RMSE by approximately 1–4% for Model\_reg and 3–6% for Model\_phy\_reg. The best conversion formulae for the asphalt and wooden slat are the custom Model\_phy\_reg used for Mini-MCA6, achieving a lowest RMSE percentage of 6.5% and 5.7%, respectively.

**Figure 8.** RMSE percentages of the general and custom NTB model-based estimated albedos of asphalt (left) and wooden slat (right).

### 4.2. Validation of Conversion Models

As mentioned in Section 2.2, avoiding the influence of the error caused by multispectral RS, the ASD measurement- and RedEdge image-based narrowband albedos were compared, as shown in Figure 9, and the accuracy of the estimated total SW albedos was evaluated, as shown in Figure 10 and Table 7.
Figure 9. Difference between the narrowband albedos derived from RedEdge multispectral images and ASD measurement.

Figure 10. Validation results of the three models estimated from RedEdge images- and ASD measurement-based narrowband albedos.

Table 7. Validation results with measures of $R^2$, RMSE, RSE, and MBE.

| Model          | $R^2$ RedEdge/ASD | RMSE RedEdge/ASD | RSE RedEdge/ASD | MBE RedEdge/ASD (Red Cross Marks in the Boxplot Above) |
|----------------|-------------------|------------------|-----------------|--------------------------------------------------------|
| Model_reg      | 0.959/0.962       | 0.0304/0.0293    | 0.0354/0.0341   | $-0.0049/-0.0113$                                      |
| Model_phy      | 0.960/0.954       | 0.0300/0.0322    | 0.0349/0.0375   | 0.0063/0.0023                                          |
| Model_phy_reg  | 0.966/0.963       | 0.0279/0.0290    | 0.0325/0.0337   | $-0.0142/-0.0179$                                      |

As shown in Figure 9, the difference between the ASD measurement- and RedEdge image-based narrowband albedos ranged between $-0.01$–$0.02$, and the most inconsistency appeared for the albedos at the NIR region. This inconsistency caused a marginal difference in the estimated total SW albedos (Figure 10).

The results estimated from ASD measured data, as shown in Table 7, demonstrated that the developed models performed well with an $R^2$ above 0.95 and an RMSE of approximately 0.03. Model_reg and Model_phy_reg showed marginally better accuracy, with the RMSE of approximately
0.003 lower than that of Model_phy. Considering that the value range of most errors is located as shown in the boxplots in Figure 10, half of the errors were located from −0.026 to −0.005 for Model_phy_reg, from −0.037 to 0.002 for Model_reg, and between −0.017 to 0.024 for Model_phy, indicating that the error distribution of Model_phy_reg was less dispersed. The scatterplots in Figure 10 show that Model_reg and Model_phy_reg may underestimate the surfaces with a lower albedo (lower than 0.03) but overestimate the higher-albedo (above 0.6) surfaces, whereas Model_phy performed better when applied to the low-albedo surfaces but probably overestimated when the albedo was above 0.4, and the overestimation may increase as the surface albedo increases.

The results obtained from the RedEdge image (Table 7) show that their accuracy is similar to the values estimated from ASD measured data with a difference of less than 0.006 in $R^2$ and up to 0.0022 in RMSE.

The suitability of the developed models to estimate the vertical surface albedos was also investigated, and the results are shown in Figure 11 and Table 8.

![Figure 11. Validation results for the samples of vertical urban surfaces.](image-url)

| Table 8. | Validation results for vertical urban surface with measures of $R^2$, RMSE, RSE, and MBE. |
|---|---|---|
| | $R^2$ | RMSE | MBE |
| | RedEdge/ASD | RedEdge/ASD | RedEdge/ASD |
| Model_reg | 0.878/0.956 | 0.0397/0.0238 | 0.0022/0.0077 |
| Model_phy | 0.827/0.856 | 0.0471/0.0430 | 0.0201/0.0295 |
| Model_phy_reg | 0.902/0.963 | 0.0355/0.0218 | −0.0110/−0.0023 |

The results estimated from the ASD measured data solely for vertical surfaces, as shown in Table 8, indicated a small difference as compared to the accuracy performance shown in Table 7. Model_reg and Model_phy_reg performed slightly better, with an RMSE reduction of less than 0.008, whereas Model_phy had the worst performance with an RMSE of around 0.01 higher. The results estimated from the RedEdge image (Table 8) indicated that their performances were inferior as compared to the ones estimated from the ASD measured data, especially for Model_reg with a difference of around 0.08 in $R^2$ and 0.016 in RMSE.
5. Discussion

5.1. Performance Evaluation

Model_reg and Model_phy_reg showed higher accuracies, suitable for SEB modeling, with RMSEs of approximately 0.02 for Sample_D (Section 3.2). As compared to the performance of another physics-based conversion model against Sentinel-2A products in urban Perugia with an RMSE of approximately 0.02 [17], Model_phy’s RMSE value was higher by 0.01 (Figure 4). This may be due to the close-to-visible wavelength for NIR channel (<1000 nm) and narrower bandwidth of spectral bands provided by UAV-based cameras, whereas the spectral bands provided by spaceborne sensors (e.g., Landsat, MODIS, Sentinel-2 MSI, etc.), to which the physics-based models are well-adapted to, could better capture the spectral variation of albedo. This resulted in an overall overestimation of SW albedos (second row, Figure 4). The degree of overestimation depends on the weighting coefficient of narrowband albedo at NIR (where the albedo is usually higher than those at VIS), which was largest for ADC-Micro and smallest for RedEdge, causing that the overestimation was highest for ADC-Micro and lowest for RedEdge.

We compared the model performance with that from previous studies, and found that the relatively low RMSEs (less than 0.033) were sufficient. To retrieve the SW albedos from Landsat 8 OLI (7 bands) data, Baldinelli et al. [47] obtained RMSE values of 0.058 and 0.039 for one regression with physics-based constraints and the other without constraints, respectively. Bonafoni et al. [17] computed the regression coefficients by applying Tasumi’s [40] strategy and directly adopted Li’s [41] coefficients for Sentinel-2 MSI (6 bands), with RMSE values of 0.023 and 0.025, respectively. Liang’s models for common spaceborne sensors revealed a high accuracy with RSE ranging between 0.01–0.02 [14].

As shown in Figure 4 and Table 5, ADC-Micro had the lowest accuracy as compared to the other cameras. This corresponds to our expectation and the previous study that less bands would influence the efficiency of converting narrowband to broadband albedos [14]. Mini-MCA6 performed best with Model_reg and Model_phy_reg whereas RedEdge performed better with Model_phy. However, their performances were similar, with the difference in RMSE less than 0.002. Their similar performance indicates that the advantage offered by Mini-MAC6’s plural bands at NIR region is not dominant to the accuracy of estimating albedo, as compared to RedEdge with the single band at NIR. Though the changes in spectral reflectance are largely in the VIS wave range, these become relatively stable in the NIR wave range. Meanwhile, spectral solar irradiance decreased from the VIS to NIR wave. Its peak was observed at around 500 nm and decreased gradually towards a longer wave range. In addition to the efficiency of the narrowband albedos to estimate albedo, the data quality, processing complexity [25], and the weight (which may influence the battery consumption of the platform and thus the available flight time) should also be considered while selecting a multispectral camera. For example, when applying the best NTB model (i.e., Model_phy_reg), the RedEdge had reduced efficiency while estimating narrowband albedos and lower spatial image resolution than Mini-MCA6, but was lighter and had a wider FOV, which may contribute to a longer flight time, reduced flight rounds, and less images to capture than the Mini-MCA6 to estimate albedos of the same area, resulting in easier and timely post-processing.

5.2. Sensitivity Analysis

As shown in Figure 5, the performance of the developed models was not much prone to solar irradiance with respect to the season and possible SZAs within the season if the UAV multispectral RS was conducted near-solar noon (late solar noon for vertical surface) and under clear skies. These results confirm Liang’s finding that broadband albedos are relatively stable unless the SZA is quite large, based on the albedo dependences of snow, deciduous forest [14], and asphalt [29], and are suitable for urban surfaces covered by other common construction materials.

As shown in Figure 6, compared to Model_phy, the accuracies of Model_reg and Model_phy_reg were less dependent on whether surfaces are horizontal or vertical. Regarding the application to
vertical surfaces with respect to various azimuths, Model_phy_reg was much less sensitive than Model_reg and Model_phy. It can be further concluded that Model_phy_reg had the least sensitivity to the applications on vertical surfaces and various azimuths.

As shown in Figure 7, different conversion models for different cameras have their own advantages with the respect to the material class, due to differences in their capacity to capture spectral variations which would cause diverse efficiency values with respect to certain spectral variations within the material class. Among them, Model_reg and Model_phy_reg could not be well-adopted to estimate the albedo of the asphalt and wooden slat surfaces. Figure 8 demonstrates the potential improvement room of a few percent in RMSE for Model_reg and Model_phy_reg due to the customization accounting for the surface material class, which was a non-negligible improvement for the case study with high requirement of estimating the albedo. It was also observed that to improve the NTB conversion accuracy, the category method of the surface cover [38,58] was also suitable for the construction material class and could be downscaled to neighborhood scales.

5.3. Model Validation

The difference between the ASD measurement-based and RedEdge image-based narrowband albedos reveals the most inconsistent at NIR band (Figure 9), which may be caused by the Lambertian surface assumption that did not consider the BRDF effect, which would have a strong influence on the NIR region, as concluded by France [59]. This inconsistency caused a minor difference in the estimated total SW albedo, as shown in Figure 10, but did not influence model validation. As discussing the error caused by ground-based multispectral RS is beyond our scope here, the results shown in Figures 9 and 10 were used to demonstrate that the developed models are applicable to the multispectral RS data in practice if adopting the appropriate observation protocols and post-processing. The following discussions are mainly based on the results derived from the ASD measurement-based narrowband albedos.

As shown in Figure 10 and Table 7, the three developed models were applicable to the independent and separate samples including both vertical and horizontal surfaces, various construction materials, and multispectral RS data with low RMSEs of around 0.03, meeting the desired accuracy of SW albedo (around 0.05) for SEB modeling. Comparing the performances of the three models for Sample_D (Figure 4 and Table 5), the performance ranking of models applied for Sample_V (Figure 10 and Table 7) showed a general consistency, but with an RMSE increase lower than 0.012, indicating that no significant difference in the developed models’ accuracies was caused by the random and independent samples.

The studies directly applying the coefficients of Liang's and others’ NTB formulae to the samples which are not used to develop the models can be regarded as model validations, where the results are supposed to show a larger error. Compared to these studies, our developed models were quite reliable with a relatively low RMSE and MBE. An average RSE of generally 0.02 for most spaceborne sensors was observed in the validation cases of Liang’s models [29]. Fitted RMSEs of 0.075 and 0.081 were shown in [47] as the results of the accuracy assessment conducted by directly using Liang’s and Tasumi’s models for Landsat 8 OLI data for estimating the albedo in urban contexts. Cao et al. [18] observed that the MBE was about 0.01 for the validation of Landsat VIS band albedo conversion algorithm given by Wang [31], applied to a UAV-based RS.

When the model validation was applied to the vertical surface (Figure 11 and Table 8), as compared to the general validation results shown in Figure 10 and Table 7, Model_reg and Model_phy_reg showed lower RMSE values than Model_phy, demonstrating that they are less sensitive to the vertical or horizontal nature of the surface.

It can be concluded that the developed models are suitable and show a relatively stable performance when applying to the separate and independent samples. However, it is not clear yet if these models only work well for Sample_V in our validation site, for which further validations are needed to draw a more general conclusion. Model_phy_reg performed better as compared to the other two models, as indicated by the RMSE values and the denser distribution of errors, revealing that Model_phy_reg
is the most stable and robust among the three models. It further suggests that the physical constraints used to develop the NTB conversion model may contribute to its applicability and robustness, which is suggested to be further applied for developing NTB conversion models for other multispectral cameras that were not analyzed in this study (e.g., Buzzard Camera six, Parrot Sequoia+ and Sentera Quad).

The technical process and method to develop the NTB conversion model herein could be applied to other cameras. The differences among Liang’s strategy of empirical regression (Model_reg), Tasumi’s strategy based on the albedo physics (Model_phy), and the improved physical strategy (Model_phy_reg) lead to different requirements to develop the models. For developing Model_reg, the sample quality and quantity would decide how general and applicable the model is. Although more samples involving diverse material and illumination conditions may result in a more compelling empirical model, the typical nature of the material and a reasonable application limit for illumination conditions (e.g., noontime as the limit used here) would efficiently reduce the workload but guarantee the model performance. Although no database of samples is required to develop the Model_phy, the specific surface orientation and solar condition of the application case should be known, which would decide the conversion coefficients of Model_phy. The specific surface orientation and solar condition of the application case should also be known for developing Model_phy_reg. However, the sample quantity would influence the Model_phy_reg much less than Model_reg, which mainly decides the variable (term explanation as shown in Table 4) with respect to the camera for Model_phy_reg.

Regarding the selection of the NTB conversion models developed here, it should depend on the similarity of the application case and Sample_D (used to develop the models) and the demand for accuracy and efficiency. If the application case is similar to the Sample_D cases considering the surface orientation, material class, and the solar condition under which it is based, Model_reg is recommended due to its high time and workload efficiency. This is because it can be adopted directly without the variation of conversion coefficients due to the illumination, unless the application priority is the accuracy (Model_phy_reg with higher accuracy as a preference). However, if there is a large difference between the application case and the Sample_D, the applicability of Model_reg should be further validated by the target case before using the Model_reg, or it may lead to a larger error due to its development strategy of empirical regression. Instead, the Model_phy_reg is more recommended to be applied in this situation, as its coefficients were decided based on the albedo physics, which would guarantee its accuracy and robustness, but with a larger workload for calculating the different conversion coefficients depending on the urban surface orientation and solar condition. However, the calculation of conversion coefficients based on the usual regular and limited surface orientation in a block or a neighborhood and fast- and easy-to-use SMARTS simulation would not be too complicated and time-consuming.

5.4. Limitation

The Lambertian assumption may be not valid for different surface covers [47]. The Lambertian assumption of the procedure to simulate spectral albedos allows us to develop models based on extensive spectral albedos under different solar conditions rather than the time-consuming and labor-intensive direct measurements of albedos using albedometers. The Lambertian assumption was used for two purposes: to obtain the spectral albedos equaling the ASD measured spectral reflectances, and to obtain the narrowband albedos equaling the narrowband reflectances derived from RedEdge images. For the first purpose, all the target urban surfaces used here are quite rough, homogeneous, without dominating 3D structures, and the ASD measurements were conducted with a near-90° elevation angle to the surfaces and with an artificial illumination to guarantee the measurement environment close to be in the laboratory, which are essential and crucial to give a Lambertian surface approximation similar to the actual situations [14,17,29,47]. For the second purpose, the albedos estimated from RedEdge images should be considered to be the Lambertian-equivalent since we did not model the BRDF effect. However, apart from the characteristics of the urban surfaces mentioned above, the RS exercises were conducted near midday (late midday for vertical surface in summer), thus
ensuring a relatively large solar elevation angle which would keep the error margin due to Lambertian assumptions low. Moreover, it would not impact our discussion (Section 5.3) as the findings were mainly derived from the ASD measured data rather than the RedEdge images. However, estimating albedos from UAV-based multispectral RS requires radiometric calibration, surface BRDF modeling (if non-Lambertian surface), and NTB conversion. The NTB conversion models developed here mainly deal with the last process, where the accuracy would be affected by the first two processes. In the future application of developed models, it is suggested that the BRDF effect be incorporated to retrieve the narrowband albedos from multispectral observation.

The developed models in this study could only be applied to the midday period (late midday for vertical surface in summer), clear sky, and the location in the mid-latitude region as they work well when applied to the validation samples. However, more samples and conditions are needed to further test the applicability of the models.

6. Conclusions

The aim of this study is to provide applicable and easy-to-use NTB conversion models for UAV-based multispectral cameras and urban textures. Based on the obtained dataset of various at-surface solar spectral irradiances and spectral reflectances of urban surfaces, we simulated extensive spectral albedos of urban surfaces (Sample_D) and thus developed three NTB conversion formulae following published methodologies (Model_reg following Liang [14], Model_phy following Tasumi et al. [40], and Model_phy_reg as an improvement of Model_phy) for three common UAV-based multispectral cameras for urban surfaces covered by construction materials. Their accuracy and sensitivities to solar conditions and construction material class were evaluated, along with the albedo retrieval capacity of three multispectral cameras. The main findings are as follows.

1. The performances of the three developed NTB conversion models are acceptable for SEB modeling (RMSE < 0.033).
2. ADC-Micro had the poorest performance. Mini-MCA6 performed the best with Model_reg and Model_phy_reg and the RedEdge performed better with Model_phy. However, their performances were similar (RMSE difference < 0.002). Data quality, processing complexity, and weight should also be considered while selecting a UAV-based multispectral camera.
3. The developed models were not prone to the solar irradiance corresponding to the season and possible SZAs within the season if the multispectral observation was taken near the solar noon (late solar noon for vertical surface) and under clear sky.
4. Model_phy_reg was least sensitive to the vertical surfaces with various azimuths, as compared to other two models.
5. The developed models performed differently for the construction material class with the RMSE percentage difference of up to 11%. The worst application targets of Model_reg and Model_phy_reg were the asphalt and wooden slat surfaces.
6. The potential for improving the customized NTB conversion models for different surface material classes could be a few percent, which is non-negligible for a case study with a high requirement to estimate albedo.

These conversion formulae were validated by independent and separate Sample_V. The main findings are presented below.

7. The developed models could estimate the total SW albedo with the fitted RMSEs of approximately 0.03, thus meeting the desired accuracy of SW albedo (approximately 0.05) for SEB modeling.
8. The model performances for Sample_V were consistent with those of Sample_D, indicating that the model performances were relatively stable when applied to an independent and random dataset.
9. Model_phy_reg’s performance was the most accurate, stable, and robust, suggesting that the physical constraint used to develop the NTB conversion model may contribute to its applicability and robustness.

All the urban surfaces studied here meet the essential and crucial conditions of Lambertian surface approximation. In the future application of the developed conversion models, it is suggested that the BRDF effect be modeled to retrieve the narrowband hemispherical albedos from UAV-based multispectral observation. It is suggested to select the appreciable NTB conversion model developed herein depending on the similarity between the application case and the samples used to develop the models in this study and the demand for accuracy and efficiency (time and workload). The developed models and technical process could contribute to the wider and further application of UAV/ground-based multispectral RS on the microclimate monitoring and SEB modeling at neighborhood or local scales. For example, before adopting the UHI mitigation strategy, quantifying the actual albedo is important to predict the strategy’s performance (e.g., outdoor thermal environment and indoor energy consumption) through SEB modeling; after applying the strategy such as the cool roof to mitigate UHI effect, monitoring the variation of albedo would support the decisions on whether to clean the dust or to repaint the roof.

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