Multi-sensor and multi-platform consistency and interoperability between UAV, Planet CubeSat, Sentinel-2, and Landsat reflectance data

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ABSTRACT
Unmanned aerial vehicle (UAV) and satellite data have considerable complementarity for platform interoperability, data fusion studies, calibration and validation efforts, and various multiscale analyses. To optimize cross-platform synergies between field-deployable UAV and space-based satellite systems, an understanding of spectral characteristics and compatibility is required. Here, we present the assessment of spectral consistency, undertaking a pixel-to-pixel similarity assessment of co-registered reflectance maps using corresponding spectral bands from UAV and satellite multispectral imagery. A high-resolution centimeter-scale UAV-mounted MicaSense RedEdge-MX sensor is intercompared against variable-resolution multi-spectral sensors on-board PlanetScope, Sentinel-2 and Landsat 8 platforms. Sampling from within an urban environment that covers a range of both natural and man-made surfaces, we employ ground-based spectroradiometer data to evaluate pixel-level responses, using regression analysis and measurements of relative root mean square error (rRMSE) to assess for factors such as spatial and spectral misalignment. Using two radiometric correction approaches for the UAV data, we found that a vicarious radiometric correction was more accurate than a linear empirical line method, with the former improving rRMSE by between 1.6% and 20.11% when assessed against spectroradiometer measurements. Spectral band misalignment between the UAV and satellite sensors affected their spectral consistency, causing different reflectance values for the same object in the corresponding UAV and satellite bands, with the issue amplified over specific land-cover classes (e.g. grass in the red edge part of the spectrum). Using the standard deviation of a UAV-derived normalized difference vegetation index (NDVI) as a metric of spatial heterogeneity, larger differences between the UAV and satellite-based NDVI were observed for different ground features in response to both land-cover boundary and shadow effects. Interestingly, higher spatial heterogeneity did not necessarily lead to higher spectral inconsistencies. It was also determined that as spatial scale differences between the UAV and satellite platforms increased, the lower was the impact of geometric misregistration on their consistency. Indeed, the rRMSE between the reflectance values of the UAV-based spectral bands and the corresponding satellite imagery was smaller at lower resolution (e.g., Landsat 8) than higher resolution (e.g., PlanetScope). Overall, the study provides insight into the collective effect of spectral and spatial misalignments on the degree of spectral consistency that can be expected between UAV and satellite data, guiding robust radiometric intercalibration efforts and the potential for improved synergy and interoperability between UAV and satellite data.

1. Introduction
Our understanding of the Earth system has been considerably advanced by the growth and development in various remote sensing platforms, including both traditional satellite-based systems, constellations of new CubeSats and the rapid developments seen via the deployment of unmanned aerial vehicles (UAVs) (McCabe et al. 2017). These data have provided the capacity for improved insights into Earth system function and behavior from local to global scales (Pádua et al. 2017; Alvarez-Vanhard, Corpetti, and Houet 2021). Individual observing systems have specific acquisition features and sensor characteristics that result in trade-offs between swath, signal-to-noise ratio, weather dependence, and spectral, spatial, and temporal resolutions. Given this, multi-sensor synergies have been utilized as a means for improving the quality and application of diverse Earth observation data, leveraging the best attributes of individual sensors and platforms to develop a stronger
combined product (Kuenzer, Dech, and Wagner 2015; Zhu et al. 2018). However, using imagery collected from multiple sensors requires spectral consistency, which can be affected by atmospheric conditions, variations in illumination geometry, sensor degradation over time, and differences in sensor characteristics (Paolini et al. 2006). Hence, radiometric calibration (also known as radiometric correction) must be applied to achieve accurate and consistent measurements to realize the full set of synergies between UAV and satellite data.

The radiometric calibration of satellite data is a process that converts raw digital numbers (DNs) into physical units, through sensor calibration, and atmospheric, solar, and topographic corrections (Liang and Wang 2019). While sensor calibration converts the sensor DNs to at-sensor radiances (Schowengerdt 2006), to compare surface features over time or across sensors, at-sensor radiances must be transformed to surface reflectance using atmospheric, solar, and topographic corrections. Many satellite image-based surface reflectance products, often produced by specifically designed radiometric correction processors, are freely available. For example, Landsat 8 Operational Land Imager (OLI) surface reflectance is generated by the Land Surface Reflectance Code (LaSRC) (Vermote et al. 2016), which uses the Second Simulation of a Satellite Signal in the Solar Spectrum (6S) atmospheric correction algorithm (Vermote et al. 1997). Sentinel-2 Multi-Spectral Instrument (MSI) surface reflectance (Level-2A) products are atmospherically corrected using the Atmospheric Correction (S2AC) processor (Richter and Schläpfer 2019) based on the LIBRADTRAN radiative transfer model (Mayer and Kylling 2005). In addition to medium-resolution satellites (e.g. Landsat and Sentinel-2), Planet’s constellation of PlanetScope CubeSats provides surface reflectance products with high resolution (i.e. ~3 m) using the 6S model with ancillary data from MODIS to perform atmospheric correction (Houborg and McCabe 2018; Planet Labs Inc 2021).

Unlike satellite-based systems that have been rigorously calibrated and validated, sensors mounted on UAVs are customized without analysis ready data products (Cao et al. 2019). Given the lack of a unified approach (Tmušić et al. 2020), users often correct UAV-based data using self-defined radiometric calibration methods, which can be grouped into three broad categories: laboratory, vicarious and empirical calibrations. Laboratory calibrations are based on physical laws that can enhance the consistency of calibrated data, but the laboratory measurements (e.g. sensor noise, vignetting, and lens distortion) are often complex and unique, which complicate their implementation and efficiency (Jiang et al. 2019b; Kelcey and Lucieer 2012). Vicarious calibrations allow users to calibrate UAV-based data through specialized software, often provided by the sensor manufacturer (e.g. Tetracam PixWrench2) or via third-party software (e.g. Agisoft Metashape and Pix4D MapperPro). While these can be automated during image processing, they tend to be opaque to users. Empirical calibrations derive reflectance based on the relationship between known reflectance’s measured from calibration panels in the field and the corresponding DNs from a UAV-based sensor (Smith and Milton 1999). The relationship tends to be either linear (Johansen et al. 2020, 2019), exponential (Abdulridha et al. 2019), logarithmic (Wang and Myint 2015), or second-degree polynomial (Crusiol et al. 2017), varying with different sensor types, land-covers, and acquisition conditions.

One area of research potential is the use of radiometrically corrected UAV data as a means to bridge the scale gap between in-situ and satellite data by providing a single intermediate observation scale to facilitate both qualitative and quantitative applications (Alvarez-Vanhard, Copratti, and Houet 2021). One example of a qualitative application may be the use of UAV imagery to identify land-cover classes in satellite imagery, providing improved capacity to produce satellite-based land-use maps (Pilaš et al. 2020; Xia et al. 2017). Similarly, a quantitative application may use UAV-based retrievals to calibrate a satellite-based model, for example to improve forest inventories (Puliti et al. 2017, 2018) or in the estimation of crop traits (Revill et al. 2020; Zhang et al. 2019). While some studies disregard potential uncertainties of UAV and satellite data for synergistic use, e.g. differences in the spectral response of individual bands and spatial heterogeneity effects (Padró et al. 2018), others have more directly intercompared retrievals (Peng et al. 2021; Tattaris, Reynolds, and Chapman 2016; Tian et al. 2017). These studies only investigated some of the advantages (and disadvantages) of UAV and satellite data in relation to particular applications or purposes (e.g. potato biomass estimation and leaf area index of mangrove forest mapping). However, few
studies have evaluated the consistency and interoperability between UAV and satellite data. Matese et al. (2015) intercompared UAV-based Tetracam ADC Lite imagery with one type of satellite data (RapidEye) to assess their similarity in retrieving normalized difference vegetation index (NDVI) values over vineyards based on a spatial statistical framework. Their study found that the NDVI similarity increases in the case of vineyards characterized by higher vegetation gradients and larger vegetation clusters. More generally, given that reflectance uncertainties might propagate to downstream products, assessing spectral consistency between UAV and satellite data is key to understanding and improving synergetic applications ( Santamaria-Artigas et al. 2021 ).

In this study, we present a novel assessment of spectral consistency, defined herein as pixel-to-pixel similarity of co-registered reflectance maps of corresponding spectral bands, between UAV and multi-platform satellite multispectral imagery over an urban residential setting capturing a range of common ground features. To do this, we intercompare a UAV-based multispectral camera (i.e. the MicaSense RedEdge-MX) with three commonly used optically based satellite platforms spanning PlanetScope CubeSat, Sentinel-2 and Landsat 8 data. We employ both vicarious and empirical calibration methods to correct the MicaSense imagery against ground-based reflectance calibration panels, and assess the resulting accuracies using separate field spectroradiometer measurements. Next, we analyze factors influencing spectral consistency between UAV and different satellite data, including spectral and spatial misalignments. Finally, we discuss the implications of spectral consistency for exploring UAV and satellite data synergies, with the aim of enhancing remotely sensed observations.

2. Materials and methods

The analysis presented herein relies on field spectroradiometer measurements (Section 2.2), UAV-based multispectral imagery (Section 2.3) and multi-scale/multi-platform satellite imagery collected from PlanetScope, Sentinel-2 and Landsat 8 (Section 2.4). All remote sensing platforms were acquired at near coincident times over a span of 4 days between November 12 and 16, 2020 ( Table 1 ). The atmospheric conditions were clear and without clouds at the times of image data acquisition. While the UAV, PlanetScope, and Landsat-8 image data were collected coincidently on November 16, the Sentinel-2 image was acquired on November 12. A justification for why the temporally displaced Sentinel-2 image was deemed suited for the analysis is provided in Section 2.4.

2.1. Study area

Data was collected across an urban residential area adjacent to the Red Sea coast in Saudi Arabia Figure 1. The study was located on the campus of the King Abdullah University of Science and Technology (KAUST), covering an area of approximately 1260 m × 480 m, with central latitude/longitude coordinates of 22.3199°N, 39.0932°E. The site is characterized by significant surface heterogeneity, and includes typical urban land-cover features, including

| Table 1. Characteristics of the UAV-based multispectral camera and of the satellite sensors used in this study. |
|-------------------------------------------|
| **UAV**                                  | **Satellite**                                  |
| MicaSense RedEdge-MX                      | PlanetScope                                    | Sentinel-2 MSI                                 | Landsat 8 OLI |
| Spectral bands (nm)                       |                                                   |                                                   |               |
| Blue                                      | 459–491                                         | 464–517                                         | 439–533       | 450 – 515     |
| Green                                     | 546–573                                         | 547–585                                         | 538–583       | 525–600       |
| Red                                       | 661–675                                         | 650–682                                         | 650–680       | 630–680       |
| Red edge (RE)                             | 711–723                                         |                                                   | 698–713 (RE1) |               |
| Near infrared (NIR)                       |                                                   |                                                   | 733–748 (RE2) |               |
| NIR narrow (NIRn)                         |                                                   |                                                   | 773–793 (RE3) |               |
| Pixel size                                | 0.1 m                                           | 3 m                                              | 10 m          | 30 m          |
| Number of pixels to cover the study area  | 12,600 × 4800                                    | 420 × 160                                       | 126 × 48      | 42 × 16       |
| Number of images to cover the study area  | 3355 per band                                   | 1                                                | 1             |               |
| Acquisition time                          | 10:05–11:29                                     | 11:15                                           | 10:51         | 10:49         |
|                                           | 16 November 2020                                | 16 November 2020                                | 12/Nov/2020   | 16 November 2020 |
2.2. Ground collected spectroradiometer measurements

To evaluate the accuracy and influence of radiometric calibration of the fine-scale MicaSense imagery (Section 2.6.1), we collected seven representative samples from each of nine sites for spectral comparison and analysis. The sites included three types of grass, trees and mangrove vegetation, gravel, sand, mangrove soil, sea water, roads, parking areas, and buildings. The region is located in a tropical arid climate with an annual rainfall of <100 mm (El Kenawy and McCabe 2016). All green areas, with the exception of mangroves, are irrigated. However, no irrigation occurred during the times for which spectroradiometer measurements and UAV and satellite data were collected across the various sites on November 12 and 16.

Figure 1. Study area at the King Abdullah University of Science and Technology (KAUST) in Saudi Arabia. Imagery presents the MicaSense, PlanetScope, Sentinel-2, and Landsat 8 images used in this study. Three sets of reflectance calibration panels and 14 ground control points (GCPs) for MicaSense image processing were placed on-site. All images are displayed as false color composites using the near infrared, red, and green bands. The location and reflectance value of each panel are shown in supplementary Figure S1. Nine homogenous sites were identified on-site, from which seven field-based spectroradiometer measurements were collected (see the location of the measurements for each site in supplementary Figure S2).

sand, gravel, mangrove soil, two grass fields, a section of asphalt-coated road, and a large concrete surface.

Figure 1. Mangrove soils consist of a combination of sand, silt, and clay (Hossain and Nuruddin 2016) and while they are usually located in the intertidal zone, the elevated mangrove soils in our study area were not subject to inundation. At each of the nine sites, the spectral responses from seven separate sample locations were collected using an ASD FieldSpec HandHeld2 spectroradiometer (Malvern Panalytical, Malvern, UK). The sample coordinates were collected using a Leica GS10 base station with an AS10 antenna and a Leica GD15 smart antenna as a rover (Leica Geosystems, St Gallen, Switzerland), providing sub-centimeter positional accuracy. The collection pattern of the seven selected samples was consistent across all sites, with 3, 5, and 7 points collected along the diagonal of a 3 m × 3 m (PlanetScope), 10 m × 10 m (Sentinel-2) and 30 × 30 m (Landsat 8) pixel size,
respectively (Figure 1 and Figure S2). The further analysis in this study used the 63 ASD samples collected within homogenous areas, while the ASD collection design, i.e. the 7 diagonal points, was to support a separate (but related) study. The ASD measurements were taken under clear sky conditions and as soon as the UAV flights were completed, which were between 11:30 and 13:50 local time. The reflectance of the selected sites is not expected to change significantly within this short time period, especially under clear-sky conditions. Moreover, spectral correction was performed using a standardized white Spectralon panel with nominal reflectance of 100% before measurement at each site, and thus compositional changes in the atmosphere would not have affected these measurements. Spectra were recorded at a consistent height of approximately 1.15 m above the ground. Given that the bare optical input of the HandHeld2 spectroradiometer has a 25 degree full conical angle field-of-view, the sampling footprint was a circle with a diameter of 0.5 m (area of approximately 0.2 m²). Three ASD reflectance spectra were measured at each of the seven samples and subsequently averaged to provide a single spectral sample. Figure 2 shows the averaged spectral response of the nine ground features (with standard deviations <0.02, Figure S3) and the corresponding bandwidth of the UAV and satellite sensors.

2.3. UAV data

2.3.1. Data collection

UAV-based multispectral imagery was collected using a MicaSense RedEdge-MX (MicaSense, Seattle, United States) multispectral camera mounted on a DJI Matrice 100 quadcopter (SZ DJI Technology Co., Ltd., Shenzhen, China). The MicaSense data consist of blue, green, red, red edge (RE), and near infrared (NIR) bands (Table 1). To ensure coverage across the entire study site, four individual UAV flights were performed between 10:05 and 11:29 local time on 16 November 2020. Each flight was carried out under cloud-free conditions, and took approximately 16 min to complete. The flight plans were designed based on previous studies (Roth, Hund, and Aasen 2018; Singh and Frazier 2018; Tu et al. 2020) to acquire UAV multispectral data suitable for integration with the satellite image data sets, i.e. to ensure that the study area could be covered by the UAV flights within close time proximity to the satellite overpasses and that the UAV data were collected over a short duration with limited changes in solar elevation and azimuth angles. Four flight lines, each with a 30 m separation, were flown for each flight. The MicaSense image data for all four flights (3,355 photos per band) were collected with 77% sidelap and 94% forward overlap. The Universal Ground Control
Station (UgCS) Client application (SPH Engineering, SIA, Riga, Latvia) was used for flight planning to collect image data, with the UAV flying speed set to 6 m/s and a flying height of 150 m, providing an approximate ground sampling distance of 0.1 m. Prior to the UAV flights, 14 ground control points (GCPs) were placed within the study area for geometric correction Figure 1, and their coordinates were measured using the Leica system. All collected global navigation satellite system (GNSS) data were processed using the Leica Geo Office software (Leica Geosystems, St Gallen, Switzerland) to achieve sub-centimeter positional accuracy. To ensure accurate radiometric calibration of the UAV data, three sets of near-Lambertian reflectance panels (19 panels in total) produced from Masonite and with reflectance intensities of 5% ~ 90% were placed within the overlapping areas of two adjacent UAV flights (Figure S1). Five ASD reflectance spectra were collected from each panel (with a standard deviation <0.016) and averaged to provide a single spectral sample.

2.3.2. Image processing

MicaSense imagery was processed using Agisoft Metashape Pro (Agisoft LLC, St. Petersburg, Russia). Initial photo alignment was conducted with the key point limit set to 40,000 and tie point limit set to 10,000. The 14 GPS-surveyed GCPs were visually identified in individual photos and used for geo-referencing of the UAV data. The camera model optimization method used model C from the study by (James et al. 2017) to avoid overfitting. The root-mean-square error (RMSE) of the geo-registration was 0.13 cm based on the 14 GCPs. The densified point cloud based on multi-view stereopsis (MVS) was then generated based on the calibrated camera positions and orientations. Ultra-high resolution (i.e. the original image scale) and an aggressive noise filter were applied when generating the MVS point cloud. The resulting point cloud was eventually used to generate a digital surface model (DSM) using a Poisson surface reconstruction method (Lucieer 2011). Based on the resulting DSM, an orthomosaic with 0.1 m spatial resolution was created.

Two radiometric correction methods, i.e. linear empirical line (Wang and Myint 2015) and vicarious radiometric correction (also called sensor-information-based calibration) (Del Pozo et al. 2014; Franz et al. 2007; Tu et al. 2018), were separately applied to create two different MicaSense orthomosaics of surface reflectance, i.e. MLinear and MVicarious, respectively. While the linear empirical correction is the most widely used radiometric correction approach to convert UAV data to at-surface reflectance, the vicarious correction has proven to provide more accurate results while also reducing the number of at-surface reflectance pixels occurring with negative values (Aasen et al. 2018; Singh and Frazier 2018; Yu-Hsuan et al. 2018). A linear empirical line correction calculates a model based on the relationship between the surface reflectance and the DN of the orthomosaic within an orthomosaic. The reflectance of the panels was calculated by resampling the ASD measurements within the full width at half maximum to match the corresponding spectral bands of the MicaSense camera. The averaged DNs of the pixels that covered each panel were calculated from the orthomosaic. A linear regression model was then generated using the least-squares method based on the linear relationship between the resampled ASD reflectance and the averaged DNs of the panels. Finally, the calculated linear model was applied to the orthomosaic to convert it from DN to surface reflectance. Compared to the linear empirical line method, vicarious radiometric correction considers the photography parameters such as exposure time to compensate the brightness variation of images and convert the DN directly to spectral radiance or surface reflectance depending on whether simultaneous irradiance measurements are available. For the capture of the MicaSense data, the exposure was manually set for each band to ensure brightness consistency and preclude saturation of the photos collected for all four flights. The equation for the vicarious radiometric correction provided by AgEagle Sensor Systems Inc (2021) is described as:

\[ L = V(x, y) \times \frac{a_1}{g} \times \frac{p - p_{BL}}{t_e + a_2 y - a_3 t e y} \]  

(1)

where \( L \) is the spectral radiance in W/m²/sr/nm; \( V(x, y) \) is the vignetting polynomial function; \( g \) is the sensor’s gain, \( t_e \) is the image exposure time; \( p \) is the normalized raw pixel values; \( p_{BL} \) is the normalized black current value; and \( a_{1-3} \) are the calibration coefficients. Once the spectral radiance is calculated, surface reflectance can be further derived by dividing the radiance with the simultaneous irradiance measurements. The signal-to-energy conversion needs at
least one known-reflectance panel for normalization. In this case, the panel with a surface reflectance of around 20% was used (Cao et al. 2019). As this conversion equation is a built-in feature of Metashape Pro, the reflectance correction method was implemented automatically when generating the orthomosaic.

2.4. Satellite data

At the time of data collection, the PlanetScope satellite constellation consisted of more than 130 individual Dove satellites that adopt the 3 U CubeSat form factor (10 × 10 × 30 cm). The PlanetScope imagery used in this study was the orthorectified analytic surface reflectance 4-band image product (PlanetScope Ortho Analytic 4B SR, Level 3B) with 3 m pixel resolution acquired at 11:15 am local time on 16 November 2020. The Collection 1 Level-2 surface reflectance product of Landsat 8 OLI was acquired at 10:49 am local time on the same day of the UAV campaign (i.e., 16 November 2020). Corresponding to the spectral bands of the MicaSense data, only the blue, green, red, and NIR bands were considered in this study (Table 1). Similarly, eight bands of Sentinel-2 data were used, including three 10 m bands covering the visible part of the spectrum, three 20 m red edge bands, and two NIR bands (one 10 m NIR band and one 20 m narrow NIR band) (Table 1). The resampling of the 20 m bands to 10 m resolution was carried out using SNAP (ESA Sentinel Application Platform). The closest available Sentinel-2A MSI Level-2A product to our UAV campaign on November 16 was acquired on 12 November 2020.

To verify the validity of the Sentinel-2 data in this study, we analyzed the time-series of Planet SuperDove analytic surface reflectance data (passing time between 10:20 and 11:10) for November 2020 (Figure S4). The standard deviation of all observations (regardless of land-cover classes and spectral bands) within November 2020 was less than 2%, indicating negligible variation in surface reflectance of the assessed land-cover classes. As the surface reflectance was near-steady during the Planet SuperDove observations in November 2020 and as the weather and atmospheric conditions were similar on November 12 and 16, we considered it appropriate to integrate the Sentinel-2 image data acquired on November 12 with the MicaSense data collected on November 16.

2.5. Geo-registration of UAV and satellite imagery

The MicaSense and satellite images were co-registered. Typically, the co-registration process includes re-projecting, resampling, geo-referencing, and cropping (Emelyanova et al. 2013; Gevaert and García-Haro 2015). In this case, all images were defined in the same coordinate system, i.e., Universal Transverse Mercator (UTM) projection and WGS84 datum. The satellite images (i.e., PlanetScope, Sentinel-2 and Landsat 8) were resampled to the spatial resolution of the MicaSense imagery (i.e., 0.1 m) using nearest neighbor interpolation, and the three resampled satellite images were subsequently used as the reference for geo-referencing (Zhu et al. 2016; Jiang et al. 2020). The MicaSense image was then geo-referenced to each of the three resampled satellite images by selecting 40 ~ 50 control points between each MicaSense and satellite image pair, respectively. The geometric co-registration was optimized by maximizing the Pearson’s correlation coefficient between all spectral bands of each image pair (Gevaert and Javier García-Haro 2015). Finally, the co-registered MicaSense and satellite imagery were cropped to cover the same area.

2.6. Comparison and evaluation of ground-based, collected UAV and satellite imagery

The ground-based ASD measurements, the collected UAV-based MicaSense data, and the three satellite data sets were evaluated and compared using the methodology workflow shown in Figure 3. First, the accuracies of the MicaSense imagery corrected by the linear empirical line and vicarious radiometric correction were assessed using ASD measurements. Next, the spectral consistency between the MicaSense and ASD simulated satellite reflectance was evaluated at the pixel level. Finally, the MicaSense images were resampled to the corresponding satellite image resolutions to assess their consistency for the whole study area. The specifics of the comparison and evaluation scheme are detailed further in sub-sections below.

2.6.1. Comparison of radiometric correction accuracy of the UAV data

As noted in Section 2.3.2, two MicaSense orthomosaics were generated using linear empirical line ($MS_{linear}$) and vicarious radiometric correction
methods ($MS_{\text{vicarious}}$), respectively. To compare the accuracy of different radiometric correction methods, a set of statistics were calculated for both $MS_{\text{linear}}$ and $MS_{\text{vicarious}}$, including the minimum, maximum, median, average, and outlier values of each band. Depending on the calibration method, some pixel values might be outside the normal range of reflectance values due to the occurrence of dark shadows or very bright features. Given that surface reflectance ranges from 0 to 1, the outliers represent the percentage of pixels with reflectance values <0 or >1. In addition, the 63 ASD measurements (9 sites, with 7 samples per site) were compared to the reflectance values of $MS_{\text{linear}}$ and $MS_{\text{vicarious}}$, which were extracted from the corresponding locations in the orthomosaics. The ASD measurements were resampled to match the spectral bands of the MicaSense camera using a Gaussian filter of spectral response functions for each band (Table 1). To extract the reflectance values of the samples from the MicaSense imagery, we created a circular mask of 0.5 m in diameter for each sample to match the observed area of the ASD spectroradiometer. The center of the circular mask was the sample position collected by the GNSS receiver. Due to the high positional accuracy of the GNSS data (0.7 cm) and the produced orthomosaics (12 cm), the location of the ASD field measurements was considered to accurately correspond to the identified locations in the orthomosaics. As all 63 ASD samples consisted of homogenous ground features, the impact of any minor spatial offsets between the field and orthomosaic measurements was considered to be negligible. All pixels within the circular mask for each sample were extracted for each band and averaged (by arithmetic mean) as the sample reflectance observed by the MicaSense camera. The accuracy of the linear empirical line and vicarious radiometric correction methods were evaluated using $R^2$ and relative root-mean-squared error (rRMSE) between the ASD measurements of the extracted reflectance values from $MS_{\text{linear}}$ or $MS_{\text{vicarious}}$.

### 2.6.2. Comparison of UAV data and ASD simulated satellite reflectance

Compared to observed remotely sensed data, simulated synthetic data allow for the isolation of the factor of interest (i.e. spectral response variations) from other perturbing effects. Here, we evaluated the isolated impact of sensor spectral properties on radiometric consistency and intentionally excluded additional effects (e.g. atmospheric effects, illumination geometries, scaling effects, etc.). Both $MS_{\text{linear}}$ and $MS_{\text{vicarious}}$ were compared to ASD simulated satellite reflectance of the 63 samples at the pixel level at the native resolution of the UAV orthomosaics (i.e. 0.1 m). The ASD measurements of the 63 samples were convolved with the spectral response functions of corresponding bands to simulate the observations from the three satellites (i.e. PlanetScope, Sentinel-2, and Landsat 8). The sources of the spectral response

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**Figure 3.** The methodology workflow of the comparison and evaluation of ground-based ASD measurements, collected UAV data and the three satellite image data sets.
functions (SRF) are listed in the data availability statement. Spectral convolution to band response functions was applied as follows (D’Odorico et al. 2013):

\[ I_{\text{simulated}}(\lambda) = \frac{I_{\text{max}}}{I_{\text{min}}} I(\lambda_i) \ast SRF(\lambda_i) d(\lambda_i) \]  

(2)

where \( I_{\text{simulated}}(\lambda) \) is the convolved spectral reflectance and \( I(\lambda) \) is the reflectance measured by the ASD at high spectral sampling.

### 2.6.3. Comparison of UAV and satellite imagery

To further assess the spectral consistency between the MicaSense and PlanetScope, Sentinel-2 and Landsat 8 data for the whole study area, both MS\text{linear} and MS\text{vicarious} were aggregated to the spatial resolutions of the three satellite image data sets (i.e. 3 m, 10 m, and 30 m, respectively) using a pixel aggregation algorithm and the nearest neighbor resampling approach. The pixel aggregation algorithm averages all pixel values that contribute to the output pixel. A point spread function (PSF) based method was also implemented to explore the potential impact of the pixel aggregation approach. It was determined that the PSF approach, which considers the characteristics of the satellite sensors (e.g. instantaneous field-of-view, point spread function, spectral response), changed the spectral response of the UAV data and calibrated UAV data to satellite-like data (Figure S5). As our focus was to compare the reflectance values of the UAV data (not satellite-like UAV data) with the corresponding reflectance values of the satellite data, the pixel aggregation method was found to be most suited to our study purpose, as it preserves the spectral response of the UAV data when resampling to different pixel sizes. Numerous research studies (Rasmus and McCabe 2018; Jiang et al. 2022; Matese et al. 2015; Thapa et al. 2021) support the use of the pixel aggregation method for preserving the spectral response of the UAV data at different spatial resolutions. Hence, the pixel aggregation method was applied herein.

Both resampled MS\text{linear} and MS\text{vicarious} data were compared to the three satellite data sets for each corresponding band. The MicaSense data from the most accurate radiometric calibration method were used for further comparisons. We assessed the impact of the spectral consistency caused by geometric registration by: 1) shifting the geo-registered MicaSense orthomosaic in 0.5 m intervals; 2) then aggregating the MicaSense orthomosaic by the pixel aggregation method to the resolution of each satellite image data set (i.e. PlanetScope, Sentinel-2, and Landsat 8, respectively); and 3) finally calculating the rRMSE in spectral consistency caused by the geometric shift Figure 4. As such, different degrees of misregistration error between the MicaSense and satellite imagery were generated. In this experiment, we shifted the geo-registered MicaSense image in both north-south and east-west directions by 0.5 m at a time and computed the resulting rRMSE values between the corresponding spectral bands of the aggregated MicaSense orthomosaic and satellite image data sets.

The impact of spatial heterogeneity on the assessment of spectral consistency was also evaluated. In this case, the spatial heterogeneity refers to the degree of spatial variability of land-cover within a satellite pixel (Wu et al. 2019). Several approaches can be used to quantify image spatial heterogeneity, such as local variance, standard deviation, variograms, and image texture metrics (including mean, variance, correlation, homogeneity, contrast, dissimilarity, entropy, second moment, etc.) (Farwell et al. 2021; Garrigues et al. 2006a, 2006b). The standard deviation is a basic and straightforward index for characterizing spatial heterogeneity and is often used as the benchmark for evaluating newly proposed methods for
exploring spatial heterogeneity (e.g. fractal, wavelet transform) (Jiang et al. 2015; Wu et al. 2016). The NDVI standard deviation of sub-pixels is an effective method to represent the spatial heterogeneity of the corresponding mixed pixel at coarse resolution (Jiang et al. 2018; Ling et al. 2016). Hence, the NDVI standard deviation (oNDVI) was used to quantify the spatial heterogeneity of the MicaSense pixels occupying the extent of the individual up-scaled mixed satellite pixels at 3 m, 10 m, and 30 m resolution.

\[
\sigma_{\text{NDVI}} = \sqrt{\frac{\sum (\text{NDVI}_i - \text{NDVI}_m)^2}{N}}
\]

where NDVI is the NDVI value of the ith sub-pixel (i.e. 0.1 m pixels from the orthomosaics) within one corresponding aggregated MicaSense image pixel resembling a satellite image pixel (i.e. 3 m, 10 m, and 30 m pixels); NDVI is the mean NDVI of N sub-pixels within one aggregated pixel; and N is the number of sub-pixels (0.1 m), i.e. 900, 10,000, and 90,000 within the aggregated pixel of 3 m, 10 m, and 30 m, respectively. The absolute error (AE) of NDVI between the aggregated MicaSense and satellite image pixels was also calculated. Higher values of \(\sigma_{\text{NDVI}}\) indicate higher heterogeneity, and lower AE of NDVI represents higher spectral consistency between the MicaSense and the satellite data.

### 3. Results

#### 3.1. Accuracy of different radiometric correction methods for UAV data

To evaluate the accuracy of different radiometric correction methods, we calculated basic statistics for the MicaSense orthomosaics corrected by the linear empirical line (\(\text{MS}_{\text{linear}}\)) and vicarious radiometric correction (\(\text{MS}_{\text{vicarious}}\)) methods (Table 2). Reflectance values of less than 0 or more than 1 were observed from the \(\text{MS}_{\text{linear}}\) for all bands. The \(\text{MS}_{\text{vicarious}}\) had no negative values but had some outliers beyond 1 in the green, RE, and NIR bands. The negative values in the \(\text{MS}_{\text{linear}}\) blue, green, red, and RE bands represented the shadows of trees and buildings while in the \(\text{MS}_{\text{linear}}\) NIR band, they occurred over water (i.e., swimming pools and the sea). The outliers larger than 1 from both \(\text{MS}_{\text{linear}}\) and \(\text{MS}_{\text{vicarious}}\) represented white building roofs. Generally, the percentages of outliers from \(\text{MS}_{\text{vicarious}}\) were much smaller (0 ~ 0.005%) than those from \(\text{MS}_{\text{linear}}\) (4.133% ~ 12.074%). Since the linear radiometric correction method is empirical and is only based on the linear relationship between the surface reflectance of the calibration panels measured by the ASD and their DNs extracted from the MicaSense orthomosaic, the linear regression model directly applied to the whole orthomosaic is prone to outliers. In contrast, the vicarious radiometric correction can compensate for the brightness variation of images by considering the photo parameters (Eq. (1)), which is more effective at adjusting the spectral outliers than the linear empirical line method.

In addition, the reflectance of the \(\text{MS}_{\text{linear}}\) and \(\text{MS}_{\text{vicarious}}\) bands were compared to the ASD measurements of the selected 63 samples Figure 5. Compared to the \(\text{MS}_{\text{linear}}\), the \(\text{MS}_{\text{vicarious}}\) reflectance had higher correlations with the ASD measurements, and a reduction in rRMSE of 1.6% ~ 20.11% was observed when using the vicarious radiometric correction. While the linear empirical line method performed well, the results indicate that the vicarious radiometric correction of the MicaSense imagery was more accurate for our particular study area.

#### 3.2. Assessment of spectral consistency between UAV and simulated satellite data at pixel level

To isolate and assess the effect of UAV-based radiometric accuracy on the relationship of UAV and satellite data, the radiometrically corrected MicaSense reflectance data produced by the linear empirical line and vicarious correction methods were compared to the ASD-simulated satellite (i.e., PlanetScope, Sentinel-2 and Landsat 8) spectral responses of the 63 samples (Figure 6). For the relationship between the MicaSense and ASD-simulated PlanetScope Figure 6a and Landsat
Figure 5. Comparison of the ASD spectroradiometer measurements and reflectance of corresponding bands from the MicaSense orthomosaics radiometrically corrected by the linear empirical line and vicarious correction methods for the 63 samples of the nine ground features.

Figure 6. Comparison of the radiometrically corrected MicaSense reflectance data produced by the linear empirical line and vicarious correction methods and the ASD-simulated reflectance of (a) PlanetScope, (b) Landsat 8, and (c) Sentinel-2 for the 63 samples of the nine ground features.
8 data Figure 6b, the MicaSense reflectance corrected by the vicarious radiometric correction had higher R^2 and lower rRMSE values than that from the linear empirical line method, especially for the blue (rRMSE difference >13%) and green bands (rRMSE difference >19%). Compared to the MS_{linear}, the MS_{vicarious} had higher correlations with the ASD-simulated Sentinel-2 data, except for the RE reflectance, where MS_{linear} had a slightly higher R^2 (difference = 0.006) and lower rRMSE (difference = 1.75%) in relation to the simulated Sentinel-2 reflectance of the RE1 band Figure 6c. That is likely due to the offset in the spectral responses between the RE bands from the MicaSense and Sentinel-2 data rather than radiometric inaccuracies.

To explore the impact of the offset in the spectral responses between the RE bands from the MicaSense and Sentinel-2 data simulated based on the ASD measurements, the relationships of different Sentinel-2 RE bands and the MicaSense RE band for all selected samples are shown in Figure 7. Regardless of radiometric correction methods, the simulated Sentinel-2 reflectance of the RE1 band (698–713 nm) had higher correlations with the reflectance of the MicaSense RE band (711–723 nm) (Figure 7(a, d)), most likely due to the closer proximity of the wavelength ranges, followed by the RE2 (733–748 nm) (Figure 7(b, e)) and RE3 bands (773–793 nm) (Figure 7(c, f)). The differences were mainly caused by the spectral response of grass samples. When excluding grass samples, the differences of the correlations between different RE bands became smaller (rRMSE differences <4.3%) than that for all samples (rRMSE differences <26.4%). That was attributed to the spectral response of vegetation showing large variations in reflectance within the RE region (690–800 nm), with increasing reflectance toward the NIR part of the spectrum as opposed to the other ground features Figure 2. Conversely, the spectral variations of all nine types of ground features were relatively small in the NIR range from 780 nm to 1000 nm Figure 2. Hence, the offset in the spectral responses between the MicaSense NIR band and the NIR or NIR narrow (NIRn) band of Sentinel-2 did not significantly influence their correlations (rRMSE differences <3%) Figure 6c. The results indicate that the relationship between UAV and satellite reflectance data will be affected by offsets in the spectral responses of their bands, with the extent of the effects being influences by the spectral properties of ground features (e.g. grass in our example), and the accuracy of the radiometric correction (e.g. MS_{linear} versus MS_{vicarious}).

**Figure 7.** Relationships of different Sentinel-2 red edge (RE) bands and the (a-c) MS_{linear} or (d-f) MS_{vicarious} RE band for all selected samples and those excluding grass samples. MS_{linear} and MS_{vicarious} are the MicaSense reflectance radiometrically corrected by the linear method and the vicarious method, respectively. The results for the other bands are shown in the supplementary Figures S6-S8.
3.3. Assessment of spectral consistency between UAV and satellite data for the study area

To assess spectral consistency between UAV and satellite data for the whole study area, the MS\textsubscript{linear} and MS\textsubscript{vicarious} were aggregated to the corresponding satellite image resolutions (i.e., 3 m, 10 m and 30 m) and compared to the PlanetScope, Sentinel-2 and Landsat 8 imagery, respectively. For all bands, the MS\textsubscript{vicarious} had lower rRMSE with the satellite images than the MS\textsubscript{linear} Figure 8. Given the offsets in the spectral responses between the MicaSense RE band and the three Sentinel-2 RE bands, the MicaSense RE imagery had the highest correlations with the Sentinel-2 RE1 image band due to the proximity in the wavelength ranges Figure 8, which is similar to the finding in Figure 6c. While the rRMSE values between the MicaSense and corresponding ASD-simulated satellite bands were similar Figure 6, the rRMSE values significantly decreased when the scale difference between the MicaSense and satellite imagery increased, i.e. from 3 m PlanetScope to 30 m Landsat 8 data Figure 8, indicating that the scale difference between two sensors might affect their spectral consistency. For example, the MS\textsubscript{vicarious} and PlanetScope imagery with the scale difference of 30 (= 3 m/0.1 m) had the largest rRMSE of 31.84% in the red band, followed by a rRMSE of 24.13% between the MS\textsubscript{vicarious} and Sentinel-2 (scale difference = 100) and the lowest rR5ME of 15.01% between the MS\textsubscript{vicarious} and Landsat 8 (scale difference = 300). Given the loss of spectral details within mixed pixels at a coarser resolution, the highly aggregated MicaSense orthomosaic at 30 m resolution had less spectral information. As such, the larger scale difference across sensors produced smaller differences of spectral information between the aggregated MicaSense orthomosaic and satellite imagery.

To assess the effect of geometric misalignments on the spectral consistency between the MicaSense and satellite imagery, the geometric misalignments

![Figure 8](image_url)

**Figure 8.** The relative root-mean-squared error (rRMSE) of the MicaSense reflectance data radiometrically corrected by the linear empirical line (MS\textsubscript{linear}) and vicarious correction methods (MS\textsubscript{vicarious}) and the corresponding bands of PlanetScope, Sentinel-2 and Landsat 8 imagery. The density scatterplots between MicaSense and satellite data for all bands are shown in supplementary Figures S9-S11.

![Figure 9](image_url)

**Figure 9.** The relative root-mean-squared error (rRMSE) between MicaSense reflectance corrected by the vicarious radiometric method and (a) PlanetScope, (b) Sentinel-2, and (c) Landsat 8 reflectance in the NIR band for each geometric shift of the MicaSense image. The bold lines show the lowest rRMSE values for non-shifted image pairs, representing the best co-registration. The results for the other bands are shown in the supplementary Figure S12.
were refined by shifting the geo-registered MicaSense image in different directions before aggregation to the resolution of the satellite image data sets. The rRMSE values between the corresponding bands of the aggregated MicaSense orthomosaic and the satellite images (i.e. PlanetScope, Sentinel-2, and Landsat 8, respectively) with different degrees of misregistration error represent the impact of misregistration on the spectral consistency Figure 9. Since the vicarious radiometric correction provided the best results, the MSvicarious orthomosaic was used for the image shifting and rRMSE calculations. Figure 9 shows the results for the NIR band, and the results for the other bands are similar (Figure S12). For each MicaSense and satellite image pair, the spectral consistency of MicaSense and satellite data decreases as the extent of misregistration increases. The larger the spatial scale factor between the UAV and satellite data, the lower the impact of misregistration was on their spectral consistency. For example, shifting the MicaSense orthomosaic 10 m eastwards increased the rRMSE between the NIR reflectance of the MicaSense orthomosaic and the Landsat 8 data by 4.05, while the rRMSE values increased by 5.88 and 9.67 when comparing the NIR band of the MicaSense orthomosaic to the Sentinel-2 and PlanetScope data, respectively.

 Considering mixed pixels of satellite imagery, the impact of spatial heterogeneity on spectral consistency between the aggregated UAV orthomosaics and the satellite imagery was analyzed using the standard deviation of NDVI (σNDVI). Due to the higher radiometric accuracy, the MSvicarious orthomosaic was used for aggregation of the pixel size to calculate the absolute error (AE) of NDVI. As shown in Figure 10, both pixels with high and low NDVI heterogeneity may have large AEs, indicating that spatial heterogeneity is not an independent factor influencing spectral consistency between the UAV and satellite data. To explicitly interpret this issue, we mapped the AE values of NDVI between the aggregated MSvicarious and satellite data (Figure 11(a-c)) and selected two typical plots as examples Figure 11d. A reduction of the NDVI differences between the aggregated MSvicarious and satellite data was observed when their scale difference became larger. The AE ranges of NDVI between the aggregated MSvicarious and PlanetScope, Sentinel-2 and Landsat 8 imagery were 0–0.65, 0–0.5, and 0–0.25 with median values of 0.084, 0.051, and 0.043, respectively. Large values of AE were mainly distributed along edges between two features with highly contrasting NDVI values (e.g. roof and garden or mangroves and water), especially at 3 m resolution Figure 11a. As the spatial resolution becomes coarser, the boundary effects were gradually reduced, which decreased the NDVI differences between features (Figure 11(b, c)). As shown in plot A in Figure 11d, large AE values in NDVI did not only appear along building edges but also occurred in the pixels consisting of both trees and their shadows. Building edges in plot A and individual trees in plot B in Figure 11d are clearly defined in the MicaSense orthomosaic at 0.1 m, with pixels of trees producing NDVI values in the range from 0.5 to 0.7 in the aggregated MicaSense image at 3 m. In contrast, trees, especially individual trees in plot B, cannot be identified in the PlanetScope image, where the corresponding area appears with NDVI values of 0.1–0.3, resulting in large differences with the MicaSense NDVI values.

Figure 10. The relationships of spatial heterogeneity and absolute errors of normalized difference vegetation index (NDVI) between aggregated MicaSense orthomosaics and (a) PlanetScope, (b) Sentinel-2, and (c) Landsat 8 imagery. The aggregated MicaSense orthomosaic used here was based on the vicarious radiometric correction (MSvicarious) method.
4. Discussion

Factors influencing radiometric consistency between UAV and satellite imagery may be caused by differences in spectral, spatial, and temporal dimensions and their interaction (Alvarez-Vanhard, Corpetti, and Houet 2021). Following is a brief overview of some of these influences, as well as some discussion of implications for future UAV-satellite data synergies.

4.1. Influential factors for spectral consistency between UAV and satellite data

4.1.1. Spectral Misalignment
Misalignments between spectral band responses represent an inherent difference between sensors and are the primary factor that affects spectral consistency when comparing spectral bands with different bandwidths, central wavelengths, and spectral response functions. Generally, the larger the wavelength overlap between spectral bands of different sensors, the higher the spectral consistency (Padró et al. 2018). However, the characteristics of spectral responses of ground features can both increase (e.g. grass for the Sentinel-2 RE2 and RE3 bands) and reduce (e.g. gravel and asphalt for the Sentinel-2 RE2 and RE3 bands) spectral inconsistencies despite offsets in the bandwidth and hence spectral responses of different sensors. Hence, the observed objects cannot be ignored when assessing the spectral consistency between sensors with different spectral responses. Our study illustrates that radiometric calibration accuracy is crucial to achieve spectral consistency between sensors. An assumption that the official surface reflectance products from satellites were of high quality, which are guaranteed by the Committee on Earth Observation Satellites (CEOS) (Lewis et al. 2018), underlies the analysis. In contrast,
the UAV-based data quality assurance is the responsibility of users, since cameras are usually calibrated by various user-selected radiometric correction methods without rigorous validation (Cao et al. 2019). Compared with the most commonly used radiometric correction, i.e. the empirical line correction method based on a small number of calibration panels, vicarious radiometric correction uses information from the whole scene. As such, the vicarious radiometric correction yielded higher radiometric accuracy that improved the spectral consistency between the MicaSense orthomosaics and satellite imagery. However, the application of vicarious radiometric corrections should be tested on a repeated basis for optimal parameter adjustment to take into account the camera performance over time, and for other sensors with different customized designs (Mamaghani and Salvaggio 2019; Yu-Hsuan et al. 2018). Of course, the radiometric quality of satellite data might also affect the spectral consistency between UAV and satellite data. Compared with high performing satellite data (e.g. Sentinel-2 and Landsat), the radiometric quality of PlanetScope data is relatively low (Rasmus and McCabe 2018), which is likely the reason for the higher rRMSE between the MicaSense and PlanetScope bands Figure 8. In this study, we only used a single PlanetScope image from one particular sensor. However, the uncertainty of cross-sensor inconsistencies should be considered when using CubeSat data for time-series comparison or synergies with UAV data.

4.1.2. Spatial Scale

A large spatial scale difference between UAV and satellite imagery is likely to make co-registration more difficult. However, the misregistration had lower impact on the spectral consistency between UAV data and those satellites with larger spatial scale differences (e.g. less for Landsat than for PlanetScope), as shown in Figure 9. According to our results, the NDVI differences between the MicaSense orthomosaic and satellite imagery did not increase or decrease correspondingly with the change in spatial heterogeneity Figure 10. That is most likely because different heterogeneous structures (e.g. the between-class spectral difference, the class-specific proportion, and the number of classes) within a coarse pixel would lead to different scale effect (Jiang et al. 2018). The spatial scale effects, defined as the phenomenon causing observations or estimates of the same object at different resolution to be inconsistent (Wu and Li 2009), naturally occur as the result of land surface heterogeneity (Tian et al. 2002; Jiang et al. 2018). Scale affects the information content of remotely sensed imagery. The NDVI differences are generally pronounced at the boundaries between two features. In addition, shadows of taller features, such as buildings and trees, could cause NDVI differences between UAV and satellite imagery. Hence, future work focusing on radiometric normalization or intercalibration of UAV and satellite data, especially for heterogeneous landscapes, will need to consider these geometric effects.

4.1.3. Temporal Stability

While the effects of spectral misalignment and spatial scale were explored in this study, the different acquisition time between UAV and satellite data should also be considered. While satellite sensors capture a single image with a wide swath at one point in time, the UAV data are usually collected over a 15–20 min period. In this case, a period of 84 min was required to collect the UAV data of the four flights to cover the whole study area. Therefore, radiometric stability during the UAV data acquisition period is essential. Often, the UAV data are collected under clear and stable conditions near solar noon to minimize changes in illumination caused by atmospheric effects or solar elevation angle, which are generally not accounted for (Jiang et al. 2019a; Svensgaard et al. 2019). However, if illumination conditions change during image capture, the radiometric calibration can become unreliable (Rasmussen et al. 2020). Moreover, artifacts will always be introduced in the process of generating an orthomosaic due to the quality of the dense point cloud, and hence also the DSM and orthomosaic (Jiang et al. 2019b; Kelcey and Luceeer 2012), especially for multi-flight UAV image stitching over a large area (Honkavaara and Khoramshahi 2018). Different blending modes or methods in UAV image processing affect the final orthomosaics (Perich et al. 2020; Cao et al. 2019). Here, we only assessed the impact of different radiometric corrections on the spectral consistency between UAV and satellite data, but the effects of individual settings and inputs into the processing chain of UAV image data to produce an orthomosaic, as well as the uncertainties of long duration data acquisitions, need to be considered in future works.
4.2. Implications for UAV and satellite data synergies

UAV and satellite data synergies focus on compensating for deficiencies of one data source based on advantages of the other to enhance observations. Alvarez-Vanhard, Corpetti, and Houet (2021) summarized four types of UAV and satellite image synergies: data comparison, multiscale explanation, model calibration, and data fusion. Data comparison is a weak synergy, as the data sets are not combined and hence no additional information is derived from comparing the two data sets (Matese et al. 2015; Messina et al. 2020; Tian et al. 2017). For the other three applications, strong synergies exist, but data intercalibration (geometric and radiometric) is a necessary precursor to ensure the quality of the results from UAV and satellite synergies (Carbonneau et al. 2020; Du et al. 2017; Belgiu and Stein 2019). Most studies of radiometric intercalibration have focused on the use of multiple types of satellite imagery. For example, Houborg and McCabe (2018) proposed a Cubesat Enabled Spatio-Temporal Enhancement Method (CSTEM) that exploits multi-source (Planet, Landsat 8, and MODIS) satellite synergies and a machine-learning method to generate Landsat 8 consistent surface reflectance at the spatial and temporal resolutions of the CubeSat acquisitions. Leach, Coops, and Obrknezev (2019) used Landsat 8 imagery as a reference image and a linear regression of invariant pixels extracted by the iteratively reweighted multivariate alteration detection method between images for the radiometric normalization of PlanetScope data. Moreover, the official Harmonized Landsat and Sentinel-2 (HLS) products provide a near-daily Virtual Constellation (VC) of surface reflectance data by combining data from both OLI and MSI (Claverie et al. 2018). In a recent example, Padró et al. (2018) used the UAV data calibrated by in-situ spectroradiometer measurements to correct Landsat 8 and Sentinel-2 data using the CorRad radiometric correction module in the MiraMon software. Alvarez-Vanhard et al. (2020) employed domain adaptation (Tuia, Persello, and Bruzzone 2016) to calibrate UAV data to make them compatible with Sentinel-2 and Pleiades data. However, apart from these studies, no other research of radiometric intercalibration between UAV and satellite data was identified.

The radiometric intercalibration of UAV and satellite data offers an opportunity to exploit UAV data to calibrate satellite data, or vice versa (Alvarez-Vanhard, Corpetti, and Houet 2021). However, both strategies remain challenging and require considerable further exploration. The differences in spatial scale are problematic when using coarse resolution satellite data to calibrate fine resolution UAV data. Spatial scale effects cannot be ignored when intercalibrating UAV and satellite imagery due to the major differences in spatial resolution. As such, scale transformation methods are required, especially considering different sensor characteristics (e.g. spectral response, instantaneous field-of-view, and point spread function). Based on high-quality coarse-resolution sensor data, the basic strategy of multi-sensor integration, including radiometric normalization and data fusion, is to apply the model conducted at the coarse resolution to the fine-resolution sensor data (Rasmus and McCabe 2018; Zhu et al. 2018). The large scale difference between UAV and satellite data (from 10 to 100s or even 1000 times) might aggravate block effects in data synergies, especially over heterogeneous landscapes with large numbers of mixed pixels (Jiang et al. 2020; Roy et al. 2008). For this issue, a multi-scale strategy, i.e. using more than two data sets of multiple spatial resolutions to bridge the scale gap, may decrease the uncertainty due to the scale divide by incorporating information at an intermediate resolution (Song and Huang 2012; Wang et al. 2017; Sun and Zhang 2019).

Single-flight UAV acquisitions cannot provide wall-to-wall data over large spatial scales, which hinders their combination with large-swath satellite imagery. Building models between UAV and satellite data requires large amounts of corresponding data, especially when using machine learning approaches. Due to the limited coverage of UAV data collected within one flight (generally <10 ha) and the large scale difference between UAV and satellite data, multi-flight UAV images with overlapping areas need to be acquired to expand the observed area and to increase the amount of coarse satellite image pixels being covered. This requires high stability of illumination conditions during the acquisition period, which can be difficult to achieve, especially in areas with persistent cloud cover, as well as urban areas with frequent tall and complex shadow-casting structures (Crusiol
et al. 2020; Wan et al. 2016; Weng 2012). An alternative strategy might be to use several partial-coverage UAV data sets distributed within a satellite image, as this approach may be likely to cover a more complete representation of landscape features within a large area (Puliti et al. 2017, 2018; Ene, Næsset, and Gobakken 2016). In addition, the settings of the flight planning variables (e.g. altitude, flight direction, speed, sidelap, and forward overlap) require careful consideration for specific applications due to their potential effects on the UAV-derived orthomosaic (Yu-Hsuan et al. 2020).

In this study, we used a manual method to ensure geometric consistency. However, manual geo-registration is often difficult and prohibitively time-consuming for time-series of image pairs. Automated registration methods available for UAV multispectral image registration may improve geometric consistency and be more time-effective (Angel et al. 2020; Meng et al. 2021; Padró et al. 2019). Such approaches include the scale-invariant feature transform (SIFT) (Lowe 1999), speeded up robust features (SURF) (Bay et al. 2008), multi-scale SIFT-RANSACT (RANdom SAmple Consensus) methods (Oh, Toth, and Grejner-Brzezinska 2011), oriented fast and rotated brief (ORB) (Rublee et al. 2011), and channel features of oriented gradients (CFOG) (Ye et al. 2019). Approaches like these may hold promise for effective and accurate geo-referencing of UAV and satellite image data. However, temporal gaps between UAV and satellite imagery may affect the accuracy of their synergies and applications. As concurrent UAV and satellite imagery may not always be available, biases between image data sets may occur, especially during seasonal and phenological transitions of vegetation and crops and in rapidly developing urban settings. Therefore, the application of coincident time-series of UAV and satellite image data sets, their geo-registration, and their temporal stability should be further explored. Likewise, suitable fusion methods are required to alleviate issues due to temporal gaps between image acquisitions.

It is obviously important to carefully select UAV sensors and develop suitable flight plans to improve data synergies and related accuracies. Current UAV-based cameras and satellite constellations are numerous and offer different characteristics and trade-offs. Hence, the spectral, spatial, and temporal fusion between UAV and satellite data should be considered before their synergies. From our study, offsets in wavelength coverage of spectral bands were the primary factor affecting spectral consistency between the UAV and satellite data. Therefore, integrating customized UAV-based cameras with similar spectral responses of satellite data, e.g. Tetracam Multispectral Camera Array (MCA) and the MAIA Multispectral Camera, may present a promising prospect to improve spectral consistency.

5. Conclusion

We present a multi-scale and multi-sensor assessment of the spectral consistency between UAV-based multispectral MicaSense RedEdge MX data and PlanetScope, Sentinel-2 and Landsat 8 data. Our analysis, undertaken across a typical urban environment with representative land-covers, quantified the impact of spectral and spatial misalignment on the spectral consistency between the UAV and satellite data sets at both the pixel level and for the whole study area. The pixel-level analysis focused on the impact of spectral effects and indicated that the relationship between UAV and ASD-simulated satellite data can be affected by spectral band misalignments as well as inherent spectral properties of the particular ground features. Considering spatial scale effects, the results for the whole study area showed that a larger difference of spatial resolution between sensors increases their spectral consistency, and that spatial heterogeneity and the boundary and shadow effects also impact data consistency between UAV and satellite data. Both pixel-level and whole-area studies demonstrated the importance of radiometric correction accuracy. The orthomosaic generated from the MicaSense data with the vicarious radiometric correction had lower rRMSE and higher correlations with the satellite data than that using a linear empirical line correction. In addition to spectral and spatial misalignments, the possible uncertainty of different illumination conditions between instantaneous satellite data and UAV imagery acquired over a period of time requires further consideration. These influential factors, in addition to the selected UAV processing steps for generating an orthomosaic, interact and collectively affect spectral consistency between UAV and satellite data. To properly benefit from the many potential UAV and satellite data synergies, robust
radiometric intercalibration remains a crucial element to reduce spectral inconsistencies.

**Author contribution statement**

Jiale Jiang: Conceptualization, Data Collection, Methodology, Investigation, and Writing – original draft & editing. Kasper Johansen: Data Collection, Supervision, Methodology, and Writing – review & editing. Yu-Hsuan Tu: Methodology, Formal analysis, and Writing – review & editing. Matthew F. McCabe: Conceptualization, Supervision, and Writing – review & editing.

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**Data availability statement**

The UAV image is available on request to the corresponding author. The satellite products were downloaded from the following public resources:

- The PlanetScope data: https://www.planet.com/explorer/
- The Sentinel-2 data: https://scihub.copernicus.eu/
- The Landsat 8 data: https://earthexplorer.usgs.gov/
- The spectral response functions were obtained from the corresponding sources:
  - PlanetScope: https://support.planet.com/hc/en-us/articles/360014290293-Do-you-provide-Relative-Spectral-Response-Curves-RSRs-for-your-satellites-
  - Sentinel-2: https://sentinel.esa.int/web/sentinel/user-guides/sentinel-2-msi/document-library/-/asset_publisher/Wk0TKajilSaR/content/sentinel-2a-spectral-responses
  - Landsat 8 OLI: https://landsat.gsfc.nasa.gov/landsat-8/spectral-response-operational-land-imager-band-band-average-relative-spectral-response

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