Article

The Potential of Moonlight Remote Sensing: A Systematic Assessment with Multi-Source Nightlight Remote Sensing Data

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Abstract: One recent trend in optical remote sensing is to increase observation frequencies. However, there are still challenges on the night side when sunlight is not available. Due to their powerful capabilities in low-light sensing, nightlight satellite sensors have been deployed to capture nightscapes of Earth from space, observing anthropomorphic and natural activities at night. To date, the mainstream of nightlight remote sensing applications has mainly focused on artificial lights, especially within cities or self-luminous bodies, such as fisheries, oil, offshore rigs, etc. Observations taken under moonlight are often discarded or corrected to reduce lunar effects. Some researchers have discussed the possibility of using moonlight as a useful illuminating source at night for the detection of nocturnal features on Earth, but no quantitative analysis has been reported so far. This study aims to systematically evaluate the potential of moonlight remote sensing with mono-spectral Visible Infrared Imaging Radiometer Suite/Day-Night-Band (VIIRS/DNB) imagery and multi-spectral photos taken by astronauts from the International Space Station (ISS), as well as unmanned aerial vehicle (UAV) night-time imagery. Using the VIIRS/DNB, ISS and UAV moonlight images, the possibilities of the moonlight remote sensing were first discussed. Then, the VIIRS/DNB, ISS, UAV images were classified over different non-self-lighting land surfaces to explore the potential of moonlight remote sensing. The overall accuracies (OA) and kappa coefficients are 79.80% and 0.45, 87.16% and 0.77, 91.49% and 0.85, respectively, indicating a capability to characterize land surface that is very similar to daytime remote sensing. Finally, the characteristics of current moonlight remote sensing are discussed in terms of bands, spatial resolutions, and sensors. The results confirm that moonlight remote sensing has huge potential for Earth observation, which will be of great importance to significantly increase the temporal coverage of optical remote sensing during the whole diurnal cycle. Based on these discussions, we further examined requirements for next-generation nightlight remote sensing satellite sensors.

Keywords: moonlight remote sensing; VIIRS/DNB; ISS; UAV; land surface; next-generation moonlight sensors

Citation: Liu, D.; Zhang, Q.; Wang, J.; Wang, Y.; Shen, Y.; Shuai, Y. The Potential of Moonlight Remote Sensing: A Systematic Assessment with Multi-Source Nightlight Remote Sensing Data. *Remote Sens.* **2021**, *13*, 4639. <https://doi.org/10.3390/rs13224639>

Academic Editors: Bailang Yu and Martin Aubé

Received: 20 September 2021

Accepted: 8 November 2021

Published: 17 November 2021

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1. Introduction

One recent trend in optical remote sensing is to increase observation frequencies to meet the urgent need for effectively monitoring of ephemeral events or phenomena on Earth from space. For example, Sentinel 2 can revisit the Earth every 10 days at the equator with one satellite, but 5 days with 2 satellites under cloud-free conditions, which results in 2–3 days revisiting time at mid-latitudes [1]. MODIS (Moderate Resolution Imaging Spectroradiometer) sensors can visit the entire Earth surface twice a day through the

constellation of Terra and Aqua, and commercial small or nano-satellite constellations, such as Jilin-1 [2] and Planet Labs' Dove [3], enable even higher observation frequencies of up to hours. Increasing the number of satellites can surely help to increase the temporal resolution of remote sensing observations, but there are still challenges at the night side, when there is no sunlight available to illuminate the Earth surface. Such a situation can be even worse in the polar regions, where sunlight is not available for almost half the year [4].

Diurnality is a common ephemeral phenomenon, frequently observed in many animals, plants, as well as some natural processes. For example, many animals' daily activities strictly depend on sunlight, and they are active during the day and sleeping at night or vice versa. Natural plants use photosynthesis to convert light energy into chemical energy during the day and uptake and transport of water through the process of transpiration at night. The ocean temperature often shows differences during the day and night cycles, mainly caused by the influences of the sun [5–8]. Diurnality (circadian rhythms for organisms) are mainly caused by day and night cycles, driven by Earth revolving both around the sun and on its own axis. Lunar rhythms are also embedded in the life cycles of many organisms. Fluctuating light levels reflected by the Moon also have a startling impact on life on Earth. For example, some animals prefer to live by the light of the Moon. For many animals, particularly birds, the Moon is essential to migration and navigation [9,10]. In addition, although coral reproduction is affected by weather, water temperature and other factors, it is also found that most corals choose to spawn during or near a full moon [11].

Human beings used to be a member of the diurnal club. During our early history, human activities at night were also greatly confined until they learned how to use fire to light up their living spaces. Artificial illumination thus has been allowing human beings to break through its natural diurnality so their social, cultural, and economic activities can extend into night, creating cities and a night-time economy [12]. Nowadays, lighting is essential for human beings, first for convenience and for safety. Artificial nightlight is thus an important and reliable indicator of human activities, directly at night and indirectly during daytime. The artificial illumination of buildings, transportation corridors, parking lots, and other elements of the built environment have become a hallmark of many contemporary urban settlements and urban activities [13].

With the advent of low-light detecting technologies, nightlight remote sensing makes it possible to detect artificial lights from space, forming a convenient and powerful tool to characterize and understand human being's altered diurnality. Since the first night-time light scene was captured using the operational linescan system (OLS) aboard Defense Meteorological Satellite Program (DMSP) satellites, detecting artificial light has become the main staple of nightlight remote sensing. Since then, whether it is mono-spectral (Visible Infrared Imaging Radiometer Suite/Day-Night-Band (VIIRS/DNB), Scientific Application Satellite-C High Sensitivity Technological Camera (SAC-C HSTC), Scientific Application Satellite-D High Sensitivity Camera (SAC-D HSC), CubeSat Multispectral Observing System (CUMULOS), Luojia1-01 (LJ 1-01), Earth Remote Observation System-B (EROS-B) or multi-spectral (Aerocube 4, International Space Station (ISS), Aerocube 5, Landsat-8, Jilin-1), new sensors have been developed with the main focus of detecting and identifying self-luminous objects at night [14].

Applications using these night-time remote sensing data include mapping urban areas [15–19], estimating population, GDP, and poverty [20–23], monitoring disasters and conflicts [24–26], as well as understanding the influence of light pollution [10,27–29]. These studies often focus on urban lights or self-luminous bodies, such as fisheries, oil, gas extraction, etc., with very few exploring the potential of nightlight remote sensing data to study natural processes.

Ironically, it seems to have long been ignored that the original purpose of DMSP/OLS was to detect clouds under moonlight illumination [30]. Although moonlight has been an important factor that affect many nocturnal animals and plants, mainstream nightlight remote sensing image processes either try their best to totally avoid moonlight, or to remove the moonlight component from observations with tuned algorithms. For example,

to generate annual DMSP/OLS composites, only sunlit and moonlight-free observations have been used, and moonlit observations are simply discarded [31]. To produce the VIIRS/DNB daily black marble product, an algorithm was developed to remove moonlight components from daily nightlight observations [32].

With the recent development of low-light detection technology, the nightlight remote sensing community started to realize that moonlight can be a very useful illumination source for detecting weather and climate parameters at night, instead of being treated as a noise source for city light detection [33,34]. Miller et al. [4] made a detailed insight of many potential applications for nocturnal low-light visible satellite observations and presented a long list of key variables that could be obtained under moonlight using VIIRS/DNB from space. They found that sometimes night-time moonlight remote sensing even showed advantages over the daytime sunlight remote sensing. These include the detection of snow cover, rainfall distributions across arid/semi-arid surfaces, the ability to peer through optically thin clouds to reveal sea ice, and the detection of oceanic currents, etc. Although these studies demonstrated a comprehensive potential for night-time low-light measurements, quantitative assessment is still needed.

How to quantitatively assess the potential of moonlight remote sensing needs a thorough investigation and more questions must be addressed. Currently, there exist many different satellite sensors, as mentioned above, with different characteristics in terms of spectra and spatial resolutions. Furthermore, drones, as a new near-ground remote-sensing platform, also have great potential to study changes in lighting at night [14]. These sensors have not been discussed for Earth observation under moonlight, thus, it is of great significance to analyze and compare them in the context of radiometric correction of nightlight remote sensing data and for the design of next generation night-time sensors. Another important question is the quantitative characterization of non-self-lighting objects under night-time low-light environments, considering that there is no rigorous quantitative analysis to date, such as land cover classification under moonlight lighting conditions.

We first compare the differences in night-time observations under moonlight using different sensors, the mono-spectral VIIRS/DNB night-time image, the multi-spectral night-time photos taken by astronauts from the International Space Station, and UAVs. We then explore the potential of nightlight remote sensing through land cover classification under night-time low-light conditions, with a specific focus on detecting non-self-lighting features at night. Finally, we propose a new concept of nightlight remote sensing—moonlight remote sensing, which uses moonlight as a stable lighting source to observe the Earth's surface, and which focuses on night-time remote sensing mechanisms and applications under lunar illumination. With these distinct characteristics, moonlight remote sensing is different than traditional nightlight remote sensing, as well as from daytime optical remote sensing.

2. Study Area and Data

The potentiality of moonlight remote sensing in this study was evaluated using two ISS multi-spectral moonlight images, acquired on 24 December 2010 and 28 November 2015; UAV moonlight imagery acquired on 20 June 2021; and VIIRS/DNB imagery acquired on 1 November 2015 (with a full moon). These images with different spatial and spectral resolutions covered three regions, Calgary in Canada, Komsomolsk-on-Amur in Russia, and a small part of the Guangming District, in Shenzhen, China. The Calgary images cover a land area of about 825.56 km², located in the south of Alberta, Canada. Calgary is the fourth largest city in Canada and is one of the most livable cities in North America in both 2018 and 2019 and has high living standards. This region has a temperate continental climate, warm in summer, cold and dry in winter, and with four distinctive seasons [35,36]. Komsomolsk-on-Amur is a city in Khabarovsk Krai, Russia, located on the west bank of the Amur River in the Russian Far East, characterized by a humid continental climate. There is a long period of snow and ice coverage because of the high latitude [37]. The Guangming District, a recently developed area in Shenzhen, has been planned as the

Shenzhen Science City in recent years and is one of the core areas for the construction of a comprehensive national science center in the Guangdong–Hong Kong–Macao Bay Area. After more than 40 years of reform and opening, the urbanization process of Shenzhen has reached a high-level with rapid economic and social development [38].

Figure 1 shows these three regions and the corresponding nightlight imagery, including information of sensor parameters. These parameters include spacecraft nadir points and altitudes, UAV height, moon altitudes, azimuths, and illumination, as well as cloud cover percentages. In addition, local times when the images were captured were also recorded. The ISS imagery was taken with digital single-lens reflex (DSLR) cameras since 2001, and was the first dataset providing colorful space-borne nightlight images with moderate spatial resolutions (often between 5 m and 200 m). The true-color images in this study were taken with Nikon D3S and D4 DSLR cameras. Both the Nikon D3S and Nikon D4 DSLR cameras were equipped with a Bayer filter in front of the sensor, and were comprised of red (R), green (G), and blue (B) microfilters. The focal lengths of the Nikon DSLR cameras in this study were 180 mm and 400 mm, respectively. These sensors, mounted on a specially designed device to compensate for the movement of the ISS, can take multi-spectral images in visible wavelengths, making it capable of detecting ground features under faint illumination from space [39–42]. In addition, a Hasselblad L1D-20c camera was mounted on a DJI MAVIC2 Pro UAV, with a focal length of 35 mm. Both Nikon and Hasselblad cameras are equipped with complementary metal oxide semiconductor (CMOS) sensors. VIIRS is a temperature-controlled charge coupled device (CCD) sensor, and is one of the key instruments aboard the Suomi National Polar-orbiting Partnership (S-NPP) satellite. It is a passive whiskbroom scanning imaging spectroradiometer, taking measurements from 0.4 to 12.2 μm in 15 reflective solar bands (RSB), including a panchromatic DNB and seven thermal emissive bands [43]. VIIRS has gathered high-quality nightlight images since 28 October 2011, at a spatial resolution of 750 m and in a broad band, covering the 500 to 900 nm spectral region for the DNB [44,45] (Table 1).

Since the ISS and UAV moonlight remote sensing images we obtained were not geo-referenced, we geometrically corrected them using Landsat-7/8 and SuperView-1 optical remote sensing data with accurate geo-referencing information. Moreover, the daytime Landsat-7/8 and Sentinel-2 and SuperView-1 optical remote sensing data were used as auxiliary data to examine the reliability of the moonlight remote sensing imagery. Landsat-7/8 and Sentinel-2 were accessed from the Google Earth Engine (GEE) platform [46], SuperView-1 constellation is China's first commercial satellite constellation with high agility and multi-mode imaging capability (<http://www.spacewillinfo.com/SuperView-1English/index.html#pos02> (accessed on 20 September 2021)).

Figure 1. Parameters of the moonlight remote sensing images in study areas.

Table 1. Acquisition parameters of the moonlight imagery used in this study.

ID	Date	LT	Lat°, Lon°	Camera	Len	City
VIIRS/DNB	4 May 2015	03:43:43	51.03, −114.03	CCD	500–900 nm	Calgary
ISS034-E-37257	29 January 2013	03:09:05	50.5, 137.5	Nikon D3S	180 mm	Komsomolsk
ISS045-E-155029	28 November 2015	00:07:23	51.03, −114.03	Nikon D4	400 mm	Calgary
UAV-Mosaic	20 June 2021	22:24–22:34	22.48, 113.56	Hasselblad L1D-20c	35 mm	Guangming

Note: LT: local time; Lat, Lon: latitude (S: −90–0, N: 0–90), longitude (W: −180–0, E:0–180); Nikon: Nikon camera; Len: focal camera lengths.

3. Methodology

3.1. Assessment of the ISS Images

We quantitatively examined the potential of ISS imagery in land surface mapping at the current stage, with a specific focus on low-light suburban areas, through an image classification process. What must be pointed out here is that we did land surface mapping using the ISS imagery as a practical way to quantitatively assess the potential of moonlight remote sensing, considering the limitations of currently available data. The whole image classification process mainly consisted of four steps (Figure 2), the geometric correction, the thresholding method to distinguish the low-light suburban areas and the bright urban areas, the multi-resolution segmentation, and the final classification step with an object-oriented method and Random Forests (RF) algorithm.

Figure 2. Scheme of the land surface classification with the ISS multi-spectral moonlight images.

3.1.1. Geometric Correction

The ISS moonlight images we obtained were not geo-referenced. We first carried out geometric correction for these images, using the Landsat-7/8 images that contain accurately geo-referenced information as the reference.

3.1.2. Retrieving the Low-Light Suburban Areas

Three different ISS image parts in the study areas were first selected to obtain the optimal thresholding values of brightness for separating bright urban areas and low-light suburban areas (Figure 3). We focused on only low-light suburban areas to avoid duplicating efforts, given that numerous studies have shown that ISS imagery is very useful to map lighting types and land surface within bright urban areas [45,47,48].

Figure 3. Multi-spectral brightness values of transects of three different parts of the ISS nightlight scenes.

In the image of Calgary, the optimal thresholding values were found to be 35 for the red band, 30 for the yellow band, and 25 for the blue band, respectively. Areas with brightness values above these numbers are bright urban areas and the others are low-light suburban areas. Similarly, the optimal thresholding values in the Komsomolsk image were found to be 50 for the red band, 50 for the yellow band, and 45 for the blue band, respectively (Figure 4).

3.1.3. Multi-Resolution Image Segmentation

We adopted an object-oriented image classification scheme, applying the multi-resolution segmentation algorithm on the ISS images first to delineate ground objects. Multi-resolution segmentation is an optimization procedure for minimizing the average

heterogeneity and maximizing the homogeneity in a given number of image objects [49]. The multi-resolution segmentation scale parameter greatly influenced the segmentation results, and the optimal scale parameter is commonly determined using a heuristic process [50]. By setting different thresholds and combining real objects, results showed that there was a relatively large area of similar land parcels. The segmentation scales of the low-light areas in the ISS image after liner stretching were finally set to 50 for the Calgary image, and 40 for the Komsomolsk-na-Amure image, respectively.

Figure 4. The images of the Calgary and Komsomolsk-na-Amure after threshold segmentation.

3.1.4. Classification with the RF Algorithm

For low-light suburban areas, we chose three types of land surface, namely snowfields (Snow), trees/forests (Forest), and other types, city lights areas (Other types). We randomly selected 200 (100 samples for training, 100 samples for testing) and 160 (76 samples for training, 86 samples for testing) samples for the land-cover classification in the two study areas, respectively. Numerous classification methods, including decision trees (DTs), support vector machines (SVMs), and random forests (RFs), have been developed for land-type classification [51–54]. RF algorithms have been widely used in various studies due to their flexibility and practicality. Many studies have found that random forest algorithms could produce better results than DT and SVM algorithms [55]. Therefore, RF algorithms were adopted in this study for object-oriented classification on the ISS images. The multi-resolution image segmentation algorithm and RF algorithm implemented in eCognition Developer 64 9.01 software was used. Some key parameters of the entire procedure are shown in Table 2.

Table 2. Parameters of the ISS image land surface classification.

ID	Geometric Correction	Threshold Values	Multi-Resolution Segmentation (Low-Light Areas)	Samples	Classification Method
ISS034-E-37257	Landsat-7	50, 50, 45	40	100, 100	RF
ISS045-E-155029	Landsat-8	35, 30, 25	50	76, 86	RF

Note: Threshold Values for the red, green, and blue bands; samples: training samples and testing samples.

3.2. Assessment of the UAV and VIIRS/DNB Images

As shown in Figure 1, we found that the UAV moonlight remote sensing mosaic eliminated the need for a linear stretching process to clearly distinguish the land surface features. Therefore, the whole image classification process mainly consisted of three steps, geometric correction, multi-resolution segmentation, and land surface classification using the RF algorithm. The coverage area of UAV moonlight remote sensing mosaic was relatively small, while each land surface type in the mosaic was too big, so that the multi-resolution segmentation in which the optimal segmentation scale was 200. We randomly selected 226 samples (113 samples for training, 113 samples for testing). Five different land surface classes (farmland, bare land, pond, vegetable greenhouses, and others) were used to map in this image.

Because the brightness ranges of VIIRS/DNB were small, numerical stretching ($\times 10^{10}$) operations were performed on the entire image. Then, the image was also selected to obtain the optimal thresholding value (170.00 in this case) for separating the low-light suburban areas from the bright urban areas (Figure 5).

For the low-light suburban area, four types of land surface were selected, namely snowy mountains (Snow), farmlands (Farmland), rivers (River), as well as other types and city light areas (Other type). The optimal segmentation scale in the multi-resolution segmentation process was set as 20. We randomly selected 189 (93 samples for training, 96 samples for testing). Some parameters are shown in Table 3.

Figure 5. The VIIRS/DNB image of Calgary before (left) and after (right, urban removed) linear preprocessing.

Table 3. Parameters of the UAV and VIIRS/DNB image land surface classification.

ID	Geometric Correction	Threshold Values	Multi-Resolution Segmentation (Low-Light Areas)	Samples	Classification Method
VIIRS/DNB	Landsat-8	1.7×10^{-8}	20	93, 96	RF
UAV-Mosaic	SuperView-1	-	200	113, 113	RF

Samples: training samples and testing samples.

4. Results

4.1. The Reliability of the Moonlight Remote Sensing Imagery

4.1.1. Visual Examination of the VIIRS/DNB Moonlight Image

Three types of moonlight imagery were used to assess the reliability of moonlight remote sensing. First, using the VIIRS/DNB image and Sentinel-2 mosaic (from 1 May 2015 to 31 December 2016) image on the Google Earth Engine platform (GEE), we first assessed the potential of multi-spectral data in land-surface classification under faint lunar illumination (Figure 6). Under a full moon and cloudless condition, the VIIRS/DNB data successfully obtained spatial distribution and spectral information of the land surface, such as snowy mountains, forests, farmlands, and rivers.

Figure 6. Three cases of the VIIRS/DNB moonlight remote sensing and Sentinel-2 images. 1. snowy mountains, 2. forests, farmlands, and 3. rivers.

4.1.2. Visual Examination of the ISS Nightlight Imagery

Comparing the ISS imagery with the Landsat-7 optical remote sensing mosaic (1 January–31 March 2013, the limitations of Landsat-7 band strips and clouds) and the Google Earth imagery in low-light suburban areas of Komsomolsk-on-Amur, Russia (ISS034-E-37257), it is very obvious that the ISS nightlight imagery with three bands well captured the ground surface in the suburban area out of the city boundaries under faint lunar illumination, in addition to the bright urban areas with emitted lights (Figure 7). However, the ground was under heavy snow cover when the ISS photo was acquired, so distinguishing more surface types in the suburbs in this imagery is very difficult. To further check whether moonlight remote sensing images are valuable under faint lunar illumination, we selected three sub-areas (A, B, and C) with different brightness and colors in the ISS image, referenced to the Google Earth image taken in the daytime in summer. Part A is mainly covered by frigid coniferous forests, making it difficult to accumulate snow on tree crowns, due to the relatively high height of the trees, blowing winds, and the sunny sides of the mountains. Part B is almost fully covered by white snow, and in the ISS image it shows a bright blue color. Therefore, part B is much brighter than part A in the ISS image, even though it was under a similar faint lunar illumination. Part C is mainly located in the city of Komsomolsk, which is the brightest and most colorful part of the ISS image.

Figure 7. The ISS nightlight image and Landsat-7 image of the Komsomolsk, Russia (above ISS and Landsat-7) and three sub-areas of the ISS nightlight image under faint lunar illumination with reference to the Google Earth images taken in summer daytime (below A, B and C).

4.1.3. Visual Examination of the UAV Moonlight Image

Finally, the spatial and spectral resolution features of the UAV moonlight remote-sensing images, obtained under a waxing gibbous moon and without any further image processing, are very vivid and comparable to the high-resolution optical images (SuperView-1) with a resolution of 1 m (Figure 8). More importantly, it is possible to obtain the same clear spatial distribution and texture characteristics of the ground surface as daytime optical remote sensing imagery, especially for non-self-lighting objects, such as fish ponds, bare ground, farmland, and even greenhouses. From part 1, although the timing of collecting data is different and the texture of the land surface changed, we could still clearly observe that both images clearly captured the spatial distribution and texture characteristics of farmland. Meanwhile, the characterization of water bodies and bare land is well reflected in the UAV moonlight remote sensing mosaic (Part2, Part3).

In conclusion, it is now feasible to capture a non-self-lighting surface under weak lunar illumination at night.

Figure 8. Three cases of the UAV moonlight remote sensing image with reference to the high-resolution optical image (SuperView-1) taken on 17 December 2019.

4.2. Land Surface Classification Results

4.2.1. Result with the Mono-Spectral VIIRS/DNB Moonlight Image

The moonlight image of VIIRS/DNB was classified to systematically explore the potential of moonlight remote sensing. The overall accuracy (OA) and kappa coefficient are 79.80% and 0.45, respectively. From the confusion matrix table, although there are some misclassifications of snowy mountains and rivers, the results (Figure 9) still demonstrate a good performance of the mono-spectral moonlight remote sensing to characterize land surface in low-light areas under full moon illumination.

4.2.2. Result with the Multi-Spectral ISS Moonlight Images

It is found that Calgary was covered by snow on 21 November and 27 November 2015. The snow-covered areas (Snow) and forests/trees (Forests) were accurately classified (Figure 10) with an overall accuracy of 87.16% and a kappa coefficient of 0.77. The classification results of the Komsomolsk-na-Amure imagery showed that the overall accuracy and kappa coefficients were 91.49% and 0.85, respectively (Figure 11). It is evident that moonlight remote sensing has tremendous potential in extracting land surfaces, such as snow-covered lands and forests, under faint lunar illumination in winter.

Figure 9. The classification result obtained in the low-light areas of the VIIRS/DNB moonlight image.

Figure 10. The classification result in the low-light areas of the Calgary image.

Figure 11. The classification result in the low-light areas of Komsomolsk-na-Amure.

Although astronauts aboard the ISS have taken numerous nightlight photos, we only found limited scenes with moonlight, mainly because their focus was on city lights. In the future, it would be very useful if astronauts aboard the ISS or China's Tiangong space station in the near future could help to take photos while paying attention to moonlit areas that are apart from urban areas.

4.2.3. Results with the Multi-Spectral UAV Moonlight Image

Finally, land surface classification with the UAV moonlight image well reflected the spatial distribution characteristics of each land type (Figure 12). The overall accuracy and kappa coefficient are 82.33% and 0.77, respectively. While some parts of the results are misclassified because of similar spectral characteristics, such as ponds and farmlands, the results prove that UAV data taken under faint lunar illumination are useful for characterizing land surfaces, particularly those that cannot emit light.

The above results have shown that these moonlight remote-sensing data could be applied well to the classification of non-self-luminous land surfaces at night.

Figure 12. The classification result of the UAV moonlight mosaic.

4.3. The Characteristics of Current Moonlight Remote Sensing

Finally, the characteristics of current moonlight remote sensing were compared in terms of bands, spatial resolutions, and sensors. The overall classification accuracy with the VIIRS/DNB imagery was the lowest among the three sets of moonlight remote-sensing imagery. By comparing VIIRS/DNB with the Sentinel-2 images (Figure 13), there are many misclassifications of snowy mountains and rivers, possibly due to their similar backscatter values in the mono-spectral VIIRS/DNB image. The result is limited by the inadequate spectrum information and substantial noise in the mono-spectral data. Thereby, multi-spectral moonlight remote sensing is expected for Earth observations under complex environments at night.

Figure 13. Comparison of snowy mountains from the VIIRS/DNB, Sentinel-2 and classification results.

In this study, three image sets with different resolutions (750 m, 30 m, 1 m) were analyzed. Comparing the classification parameters and results, we found that the higher the spatial resolutions were, the more details of the features in an image could be shown, and the UAV image showed unexpectedly vivid details that are even comparable to daytime high-resolution images. Even cars parked in parking lots could be clearly seen on the UAV moonlight image (Figure 14). However, the single-scene data only covered a small amount of land surface. To cover a larger area with more than one scene, the image quality of the multi-scene data could be reduced significantly. Small changes in georeferencing and the surrounding environment caused some land cover types to be misclassified.

Figure 14. Cars in the UAV moonlight image acquired on 20 June 2021.

Finally, panchromatic VIIRS/DNB with a spectral coverage from 0.50 μm to 0.90 μm uses a unique detecting technology. DNB measures night lights, reflected solar, and/or moon light with a large dynamic range of 45,000,000:1, which allows the detection of reflected signals from as low as a quarter full moon illumination to the brightest daylight. To achieve this large dynamic range, it uses four charge coupled device (CCD) arrays in three gain stages.

As a comparison, consumer-level digital CMOS cameras from Nikon and Hasselblad are used to obtain land surface images under faint lunar illumination (Table 4). It was found that the further the imaging distances are, the larger the International Organization for Standardization (ISO) values are. The exposure time of the UAV imagery is the longest, while that of the ISS imagery is relatively short. The aperture value (AV) and white balance (WB) were F/2.8 and auto-adjustment, respectively. Compared with the VIIRS/DNB sensor, the cost of the UAV and ISS cameras were greatly reduced and they had additional advantages, such as more spectral bands (RGB color) and finer spatial resolutions. However, given the relatively long exposure time, it is impossible to apply a carpeting data acquisition mode to ISS cameras as what is currently implemented for VIIRS/DNB to collect land surface data without gaps under faint lunar illumination.

Table 4. Parameters of different moonlight sensors.

ID	Camera	Len	ISO	Exposure	AV	Distance	WB
ISS026-E-12438	Nikon D3S	180 mm	12,800	1/15S	F/2.8	409 KM	Auto-adjustment
ISS045-E-155029	Nikon D4	400 mm	10,000	1/25S	F/2.8	394 KM	Auto-adjustment
UAV-Mosaic	Hasselblad L1D-20c	28 mm	3200	1S	F/2.8	120 M	Auto-adjustment

5. Discussions

5.1. The Potential of Moonlight Remote Sensing to Increase Temporal Resolution

Undoubtedly, our study strongly demonstrates that moonlight remote sensing in the detection of non-self-emitting objects at night is feasible. For example, using either VIIRS/DNB or ISS moonlight data, moonlight remote sensing could be used to identify snow glaciers. In recent years, the continuous melting of glaciers has posed more serious problems for human habitats, as well as for climate change. Due to the limited night-time observation data, the melting rate of permanent glaciers at night has not been extensively studied [41,56,57]. Thus, there is a great potential for nightlight remote sensing in glacier studies.

Our findings further support calls for a newer generation of nightlight sensors [58,59], but also strongly suggest that attention should be paid to detecting reflected moonlight from land surface outside of urban areas. With advanced low light detecting capabilities, these sensors will help to fill the observation gaps on the night side of a full orbit cycle for optical satellites. Currently, Landsat and Sentinel-2 sensors apply a mechanism to shut down when the satellites enter the night side, leading to a huge waste of orbit resources.

To efficiently utilize moonlight as a useful remote sensing illuminating source, we must rely on the advent of light-sensing hardware technologies. As shown above, thanks to its improved sensitivity, VIIRS/DNB allows the detection of moonlit features out of urban areas. However, its band settings are still limited to a broad band and its spatial resolution is still relatively coarse (750 m), to guarantee enough light energy to be captured during a relatively short period of a single scan. The ISS and UAV sensors can capture photos in three bands and with finer spatial resolutions, but require much longer exposure times. These technical limitations are expected to be overcome soon with advancements in light-sensing hardware technology.

5.2. Technical Speculations for the New Generation of Nightlight Satellite Sensors

5.2.1. Spectral Resolution

Although, it is highly convincing that moonlight can be a very useful illuminating source for Earth observations via optical remote sensing. Our knowledge of utilizing moonlight for remote sensing purposes is still very limited. We have proposed some new views and ideas for future designs of nightlight satellite sensors. First, for detecting nightlight non-self-emitting objects, the current mono-spectral nightlight remote sensing data are very limited and more bands are required. We believe that the bands of future sensors must contain at least three bands in the visible range, as well as a near-infrared band (IR). With three bands, the ISS and UAV data can overcome the limitations of traditional mono-spectral VIIRS/DNB data [46–48]. Whether for urban lighting or light pollution, a single wide waveband is no longer able to meet our requirements. It has been discussed that the scotopic band from 0.454 to 0.549 nm, the photopic band from 0.51 to 0.61 nm, and a broad red and near-infrared band spanning from 0.61 to 0.9 nm are needed for future sensors. Additionally, IR bands are also needed to detect sodium vapor emission lines [57]. Combining the current experience of lightings in urban areas [58], the perspective of light pollution [59] and this study, the settings of a new generation of nightlight satellite mission should contain at least four-color channels in the visible light band (at 383–503, 493–619, 568–584, and 797–833 nm), and an additional ~10 μ m thermal infrared band for cloud and fire detection.

5.2.2. Spatial Resolution

The optimal resolution settings of remote sensing sensors should be 30 m or 10 m, similar to those discussed in the Nightsat proposal [57]. The spatial resolution of UAV nightlight sensors and the Jilin-1 sensor are now able to achieve spatial resolutions finer than 1 m, which is significant for small-scale urban characterization, especially the extraction of street lights [60]. However, the higher the spatial resolution is, the smaller the field of view is. Based on previous analyses and discussions, we suggest setting the optimal resolution at 10 m or 30 m due to the following reasons: (1) there are now a large amount of daytime optical Landsat series and Sentinel-2 data, which could be well applied to both urban refinement mapping and global mapping; (2) traditional optical remote sensing, however, is not available for research with nightlight Earth observation; (3) nightlight imagery can be effectively combined with daytime optical imagery to increase the capability to characterize land surfaces [61,62]. Our future nocturnal and daytime optical data will be complementary, enabling more applications of circadian studies. Furthermore, setting similar spatial resolutions for both nightlight and daytime optical imagery will also reduce the burden of image processing.

5.2.3. Imaging Sensitivity Requirement

Both DMSP/OLS and VIIRS/DNB needed to apply the single wide spectral band strategy to gather as much light energy as possible during a single scan to increase the sensitivity. How to increase the number of bands and sensitivity at the same time might be a very large challenge for next generation nightlight remote sensing satellite sensors.

To face this challenge, ISS astronauts applied a specially designed tool to compensate the movement of the ISS to increase exposure time. However, such an imaging strategy obviously cannot take observations in a carpeting mode. That challenge is expected to be solved in the near future with the development of photo sensing materials and technology. On the other hand, the VIIRS DNB sensor is a temperature-controlled charge coupled device (CCD), provides global daily measurements in single nocturnal visible and near-infrared (NIR) band that is suitable for Earth system science and applications studies. One thing that must be pointed out is that VIIRS/DNB only has a mono-spectral band, which is still below the spectral band requirement for detecting all types of city lights with a diverse range of spectral characteristics. In addition, it takes 0.56 s for the instrument to scan across the width of the swath. During this time, the nadir point of the satellite moves 3.75 km (the satellite moves at ~6.7 km/s). In the future, if equipped with a multi-spectral sensor, how to maintain the same level of sensitivity with reduced light energy will be the primary problem to be solved.

6. Conclusions

Most nightlight remote-sensing studies focus on artificial lights that are emitted at night and can be observed from space, especially those of cities. Little attention has been paid to examine the potential use of reflected moonlight. The present study systematically evaluated the potential of moonlight remote sensing.

(1) The reliability of the moonlight remote-sensing imagery.

Using VIIRS/DNB, ISS and UAV moonlight images, the possibilities of moonlight remote sensing were discussed. VIIRS/DNB data successfully acquired spatial distribution and spectral information of land surface, such as snowy mountains, forests, farmlands, and rivers. The ISS data successfully identified snow and forests in the wilderness. In addition, the spatial distribution and texture characteristics of the land surface could be obtained as clearly as optical data in the daytime, especially for the observation of non-self-luminous objects, such as fish ponds, bare land, farmland, and even greenhouses. Therefore, it is believable that moonlight remote sensing is feasible for obtaining non-luminous land surfaces under faint lunar illumination at night, providing a practical way to increase observation frequencies of optical remote sensing.

(2) Land surface classification of moonlight remote-sensing imagery.

VIIRS/DNB, ISS, UAV images were classified to explore the potential of moonlight remote sensing. The overall accuracy (OA) and kappa coefficient of the VIIRS/DNB moonlight image are 79.80% and 0.45, respectively. In the low-light suburban areas of Calgary, the overall accuracy and kappa coefficient of the classification result are 87.16% and 0.77, respectively. While the overall accuracy and kappa coefficient of Komsomolsk-na-Amure are 91.49% and 0.85, respectively.

The land surface classification of UAV moonlight images well reflected the spatial distribution characteristics of each land type. The overall accuracy and kappa coefficient are 82.33% and 0.77, respectively. The above results show that these moonlight remote sensing data can be applied well to the classification of a non-self-luminous land surface at night.

(3) The characteristics of current moonlight remote sensing.

Finally, the characteristics of current moonlight remote sensing were compared from three aspects of bands, spatial resolutions, and sensors. First of all, multi-spectral moonlight remote sensing is more suitable for Earth observation under complex environments at night. Then, the spatial resolution of the moonlight data directly affects the application scenario of moonlight sensors; both CCD and CMOS cameras have great potential to achieve night-time Earth observations under fine lunar illumination.

The present study has systematically proved the huge potential of moonlight remote sensing in detecting non-self-emitting objects at night, which has been overlooked in traditional applications of night-light remote sensing. Although moonlight remote sensing has great potential for Earth observations, there is still more work to be done to use moonlight as an illuminating source for nightlight remote sensing. It is more difficult for the nocturnal atmospheric radiative transfer model to establish that the moonlight irradiance is much smaller than the sunlight irradiance and atmospheric changes at night are more complicated. In addition, the irradiances of moonlight under different moon phases from a new moon to a full moon also need to be carefully measured and calculated in the future. Meanwhile, studies on the nocturnal atmospheric radiative transfer model and the influence of different moon phase irradiances on the quality of nightlight data are also the basis for promoting quantitative research of moonlight remote sensing.

Author Contributions: Conceptualization, D.L. and Q.Z.; methodology, D.L. and Y.W.; writing—original draft preparation, D.L., Q.Z. and J.W.; writing—review and editing, D.L., J.W., Y.S. (Yanyun Shen) and Q.Z.; supervision, Q.Z.; project administration, Q.Z. and Y.S. (Yanmin Shuai); funding acquisition, Q.Z. and Y.S. (Yanmin Shuai). All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Key Research and Development Program of China (No. 2017YFB0504204; No. 2020YFA0608501); the Talents Recruitment Program of the Chinese Academy of Science (No. Y674141001; No. Y938091); and supported in part by the National Natural Science Foundation of China (General Program, No. 42071351), the Liaoning Revitalization Talents Program (No. XLYC1802027), the Western Talents (No. 2018XBYJRC004), and the Discipline Innovation Team of Liaoning Technical University (No. LNTU20TD-23).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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