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Monitoring mangrove phenology using camera images

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Abstract. Mangrove conservation is known as a significant means of sequestering atmospheric carbon dioxide to help mitigate climate change. Recently, a network called "Phenocam" has initiated the use of low-cost camera photos to monitor vegetation phenology world-wide. Despite that Phenocam has been proved to be feasible and useful for many tree species, to the authors' knowledge, the Phenocam approach has not been tested on mangroves. In this paper, we first collected two months of repeated digital camera photos capturing mangroves in the Mai Po Nature Reserve (MPNR), Hong Kong. Then, vegetation indices were extracted from the camera photos and validated with in situ measured NDVI. The feasibility, effectiveness, and potential biases of using camera photos to monitor the phenology of mangroves are discussed.

1. Introduction

The mangrove is a specific type of tropical and subtropical tree species having substantial reproductive adaptations that allow it to colonize and develop in saline, hypoxic environments. Vegetation phenology has been a focus of attention in recent years because of its linkage to plant biogeochemistry[1]. The earth is expected to warm up by 5°C on average in the next 100 years, and around 60% of the increase is attributable to carbon emissions [2]. Mangroves take only 0.1% of the earth's surface [3]. However, if all mangrove habitats were destroyed on the planet, the atmospheric CO_2 concentration would be 2.5 times higher than its current level [4]. As a result, monitoring mangrove phenology and investigating the pattern in its cycle play crucial roles in understanding the carbon dynamics in mangrove wetlands. The greenness of vegetation in a particular area is a sound indicator of the vegetation phenology.

Conventional measurements of vegetation phenology were based on field records of biological events such as bud-burst, flowering, seed set and leaf senescence [5]. To apply them in a mangrove wetland requires labor-intensive work. Despite the accuracy and reliability of the in-situ measurements, they can be expensive and require special expertise to operate correctly and so it's difficult to achieve a broad geographical and temporal coverage. Remote sensing from the space is another source to produce specific images of the forests with better spatial and temporal resolution than in-situ approaches. However, satellite images are significantly disturbed by bad or cloudy weather, especially for tropical and sub-tropical areas like Hong Kong where clear sky is rare due to its long rainy season. Recently, a network of fine-resolution digital cameras installed in the field known as "Phenocam" emerged as a new method to monitor vegetation phenology [6]. Compared to classical methods, the Phenocam approach has two main advantages. First, Phenocam is cheap and easy to operate since it only requires photos taken by regular commercial cameras to generate time-series measurements of



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vegetation phenology. Second, camera photos taken below the cloud boundary are free from the cloud influence, and thus, can provide a quasi-continuous time-series of vegetation phenology with temporal resolutions varying from minutes to hours. The fine temporal resolution enables plant physiologists to investigate high-frequency variations of canopy phenology. Many existing studies have proved the feasibility and effectiveness of monitoring vegetation phenology using camera photos and the Phenocam approach [6][7][8], but the method has not been tested on mangroves yet.

This paper investigated and discussed the feasibility, effectiveness, and potential bias in using camera photos and the Phenocam approach to characterize the phenology of mangroves. Taking the Mai Po Nature Reserve (MPNR), Hong Kong, China, as the study area, we first collected a time-series of camera photos focusing on mangrove canopies for two months in Summer and Winter, under systematic data quality control. Then, two vegetation indices, Green Chromatic Coordinate (GCC) and excess GCC (ExGCC) were extracted from the camera photos and validated with in-situ measured Normalized Difference Vegetation Index (NDVI).

The remainder of this paper is organized as follows. Section 2 introduces the study site, data collection, data quality control, and analytical methods used. Section 3 presents the results of mangrove phenology monitoring using camera photos and validation results compared with NDVI. Section 4 discusses the effectiveness and potential risks of such phenology monitoring. Section 5 concludes.

2. Methods And Materials

2.1. Study Sites

The study site, managed by the World Wide Fund For Hong Kong and Hong Kong Police Force, is located at the core zone of Mai Po Nature Reserve (MPNR), which is at the corner of Hong Kong SAR, China. As part of the Inner Deep Bay Ramsar wetland, MPNR is of international biological importance.

Mangroves in MPNR cover an area of 115 hectares, the largest among all mangrove stands in Hong Kong. Our study area is dominated by two native species, *Kandelia obovata* and *Acanthus ilicifolius*. The *K. obovata* are aged 25-30 years. The canopy height averages 6.7 m with a diameter at breast height (DBH) of 7.6 cm, and the forest density is 0.7 trees m⁻². *A. ilicifolius* scatters at the understory of *K. obovata*, reaching a maximum height of 2 m. In mangrove sediments, total organic carbon contents are 34.3 g per kilogram of soil at a depth of 0-10 cm and 31.1 g per kilogram of soil at 10-20 cm. The semidiurnal tide is a factor influencing the growth of mangroves. According to a two-year result from monthly-based field campaigns that records the volumetric soil moisture content of sediments when exposed to air, the mangroves experienced a consistent wet condition (45.7% 1.2%, mean standard deviation, n = 186). Hydrology in MPNR is also primarily influenced by the Pearl River, the largest river in southern China.

The mean annual temperature was 23.3 °C, and yearly rainfall averaged 2399 mm from 1981 to 2010 in Hong Kong (https://www.hko.gov.hk/cis/normal/1981_2010/normals_e.htm), indicating a typically humid tropical climate. Wet seasons start from April and end by September, and dry seasons begin from October and end by March (Tang, 2006)[9]. For wet seasons, mean monthly temperature is above 25°C, while 86% of rainfall concentrates in this period. What is noteworthy is that the annual rainfall at MPNR is lower than the rest of Hong Kong because it is under the rain shadow of the Tai Mo Hill.

2.2. *Data*

2.2.1. Data Collection.

A digital camera was installed in a fixed position on top of a meteorological tower. It was leveled with the horizon with a view across the top of the canopy. This Wingscapes Timelapse Cam provided JPG images at 30-min intervals for daytime. Each image has three color channels of 8-bit RGB color information and for each channel digital numbers (DN) ranging from 0 to 255. Cameras operated in the automatic aperture and exposure mode. The timestamps of all images were extracted from the

Exchangeable Image File Format (Exif) information stored along with the images. The Exif data stores the basic information about the image, including image gamut space, capture time and save time. We save all the capture times to a timestamp dictionary for fast queries. In total, we captured 1045 images in the period of February 2017 and July 2017. Figure 1 shows two examples of images.



Figure 1. Camera Picture Examples.

2.2.2. Data Quality Control.

Camera, Aperture, and Exposure. We ensured that the camera's position and direction remained constant all the time during the whole period. The time series of photos was first visually inspected for camera shifts and the related changes in field of view (FOV) [10]. The FOV remained mostly unchanged. However, some more significant alterations in the FOV were observed as the direction of the camera skewed a few times throughout the study.

Illumination Conditions. We also observed images with unusual illumination which may affect the calculation of vegetation indices. For example, images before sunrise and after sunset had inadequate

lighting and so could hardly be used for monitoring the greenness. Also, images around the sunrise and sunset had significant different hues.

To filter out the bad-quality images that were significantly affected by camera shifting or unusual illumination, we calculated the percentage of green color in each image as an indicator for filtering. The percentage of green color was computed as the percentage of image pixels where the digital number of green channel DN_g was smaller than 175. After applying the greenness proportion calculation to one month's images, we found that the proportions are segmented into two parts. Irregular images suffering from inadequate illumination or camera shifting problems had values close to 1, while the normal ones were normally around 0.6. Therefore, we selected a benchmark of 0.75 to sift out the high-quality images to be used in further calculations (Figure 2). The threshold value can vary significantly depending on the position and direction of the camera. In this study, we selected based on the histogram of the fraction of green color and picked 0.75 as the threshold. Later visual inspection confirmed the effectiveness of the proposed data cleaning method. Using this filter, we identified and removed 422 images from the original dataset. Rechecking the identified bad images, we found that they are all ill-illuminated and had a time span from 6 pm to the next day's 6 am.

Moreover, at the bottom of each image, a black bar is attached to display the time, temperature and equipment manufactory, which largely disturbed our calculation of vegetation indices. Noting these noises, images were first cropped to exclude the bars. The way to solve the field of view shifts is discussed in later sections. All image processing was conducted using Python 3.6.



Figure 2. Data cleaning using the fraction of green color. Images with more than 75% of non-green colors were excluded from follow-up analysis. The x-axis represents the proportion of non-green color pixels in each image.

2.3. Extracting Vegetation Indices from Camera Photos

To quantify canopy greenness, we calculated the green chromatic coordinate (GCC) [11], which is widely used to monitor canopy development and is strongly related to Global Primary Production (GPP) (Pastor-Guzman, 2018)[12]. The GCC index can be denoted as follows,

$$GCC = \frac{DN_g}{DN_r + DN_g + DN_b}$$
 Equation (1)

where DN indicates the digital values at respective channels of the images, and the subscripts R, G, and B indicate the red, green, and blue channels, respectively.

We also computed another vegetation index, the excess green chromatic coordinate (ExGCC) [13], which can be denoted as follows,

$$ExGCC = 2DN_g - (DN_r + DN_b)$$
 Equation (2)

ExGCC can be less noisy than GCC in some ecosystems, notably in conifer canopies [14], although GCC is generally more effective than ExGCC in suppressing the effects of changes in scene illumination [14]. Due to the formulas, all the GCCs larger than 1.0 were discarded. All the ExGCCs greater than 200 were modified to 200.

2.4. Time-Series Smoothing

Knowing the vegetation indices (VIs) were sensitive to illumination conditions, we extracted them from the images taken between 10 am and 2 pm to avoid the biases caused by sunset when stable illumination is unavailable. We applied a moving window smoothing to the extracted VIs to highlight the underlying monthly and seasonal change patterns by removing several outliers caused by unexpected fluctuations that appeared in the extracted time series of GCC and ExGCC caused by factors such as light illumination disturbance, droplets on lens, and cloud. Several smoothing methods including the mean filter, median filter, and 90% percentile filter were applied for comparison. We used in situ half-hour NDVI data for validation. A three-day moving window was applied to smooth it [12]. The results were shown in Table 2. The validation will be conducted by the Pearson Correlation Coefficient and Room Mean Squared Error (RMSE).

3. Results

3.1. Extracted Vegetation Indices of Mangroves

We obtained the GCC (Figure 3) and ExGCC (Figure 4) of mangroves from camera images and smoothed them for the two entire months of February 2017 and July 2017. Table 1 shows the descriptive statistics of the extracted GCC and ExGCC.

The extracted GCC of mangroves ranged from 0.342 to 0.370, averaged at 0.360 and had a standard deviation of 0.007 in February 2017. In July, GCC ranged from 0.342 to 0.396 with an average of 0.361 and a standard deviation of 0.009. ExGCC was on a different scale. ExGCC in February ranged from 4.9 to 36.8, averaged at 19.6, and had a standard deviation of 6.7. In July, the ExGCC ranged from 10.7 to 66.7, averaged at 34.6, and had a standard deviation of 8.9.



Figure 3. Extracted GCC of mangroves in February and July, 2017 before and after data smoothing.

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Figure 4. Extracted ExGCC of mangroves in February and July 2017 before and after data smoothing.

	Feb GCC	Feb ExGCC	July GCC	July ExGCC
Count	26	143	117	260
Mean	0.359	19.6	0.361	34.6
Std	0.007	6.7	0.009	8.9
Min	0.343	4.9	0.342	10.7
25%	0.357	14.7	0.354	28.2
50%	0.360	19.6	0.358	36.3
75%	0.365	24.1	0.367	40.5
Max	0.370	36.8	0.396	66.7

Table 1. Summary of extracted GCC and ExGCC in February and July 2017.

Both GCC and ExGCC were relatively stable during both months, while we still observed some minor fluctuations that lasted for days. For example, we observed significant decreases in GCCs on about July 10th and 19th, which were confirmed to be rainy days according to local weather records. In February, the largest values appeared in the middle of the month and on July 23rd.

Table 2. Examples of raw and smoothed NDVI time series.

Time	NDVI	meanNDVI	medianNDVI	qNDVI	
2016-03-09 14:00:00	0.841	0.830	0.829	0.858	
2016-03-09 14:30:00	0.859	0.830	0.828	0.858	
2016-03-10 10:00:00	0.826	0.837	0.828	0.858	
2016-03-10 10:30:00	0.816	0.837	0.828	0.858	
2016-03-10 11:00:0	0.799	0.837	0.828	0.858	

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3.2. Seasonal Difference

Since February and July are representative months of winter and summer, respectively, we summarized the potential seasonal effects on mangroves by comparing these two months' statistics and trends.

The mean value of the ExGCC increased from 19.62 in February to 34.63 in July by about 76.5%, indicating a greener canopy. However, we only observed an increase of about 2%, for GCC, from February to July. We applied the Two-sample t-Test to check statistical significance of the difference between GCCs in these two months, with an alternative hypothesis that the average GCC in February was greater than that in July. It turned out that the p-value of this test was about 0.302, signifying that there is no sufficient evidence to prove that the mean GCC in February was different from that in July. Also, July's ExGCC has higher standard deviations, for about 8.94, compared with 6.71 of that in February, meaning that high temperatures and more significant day and night temperature difference made the VIs in July have larger values and standard deviations.

When looking for trends from the Figure 1 and Figure 2 of smoothed vegetation indices, we found that the mean GCC in July had risen from 0.3772 to 0.3895, different from the drop in February, which started from 0.3472 to 0.3431. It means that GCCs and ExGCCs had quite positive relationships with the temperatures. The same trends can be displayed more significantly using ExGCCs.

3.3. Validation Results

We validated the VIs extracted from the photos with *in-situ* NDVI measurements. The correlation coefficient between the time-smoothed GCC and *in-situ* time-smoothed NDVI was about 0.252 in February and 0.351 in July. If we look at both months, this model has a correlation coefficient of about 0.7921. We chose quantiles because they behaved the most stably and were not affected by extreme values. These two months both presented positive correlations, demonstrating that the Phenocam method's moderate effectiveness in predicting field vegetation indices.

Effects of Exposure Time. When scanning all the images for visible stains, we found that they had different exposure times, which might lead to varying illumination conditions that affect the magnitude of extracted indices. We, therefore, extracted the exposure times from images' Exif data and computed their correlation between GCCs and ExGCCs and in-situ NDVI values controlling the effects of exposure time, as presented in Table 3. The correlation coefficient between time-smoothed GCC and NDVI increased to 0.8250 in February and 0.7108 in July, Figure 5, indicating that the Phenocam method can provide accurate monitoring results of mangrove phenology with controlled exposure times.

		5	I	0			
	coef	standard	t	P > t	[0.025	0.975]	
		error					
const	0.7085	0.003	248.3	0.000	0.703	0.714	
x1	-0.0260	0.011	-2.463	0.014	-0.047	-0.005	
x2	0.0248	0.004	5.896	0.000	0.017	0.033	

Table 3. Ordinary Least Square Regression Results of NDVI.

4. Discussions

4.1. Pros and Cons of Using Camera Photos to Monitor the Growth of Mangroves

After Comparing the Phenocam method with others like Landsat data, we found that we could detect the potential drawbacks of the clear digital images more swiftly and directly and correct them as soon as possible. Using digital images is also an economic research method that can be used in other scientific cases and save a lot of money if the vegetation indices are representative of one type of ecosystem [15][16].

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As a result, a number of researchers applied this method to their interesting vegetation. According to Sara Helen Knox [14], Phenocam-based indices were calculated on two wetlands, West Pond and Mayberry. The West Pond was characterized by a mix of emergent marsh species, including Schoenoplectus acutus and Typha species. The Mayberry site was more spatially heterogeneous, consisting of an intermixing of open water and vegetation patches. It also comprised Typha sp. and Schoenoplectus acutus. The generated GCC in West Pond had a correlation of 0.88 with local GPP, compared to 0.65 at Mayberry. As the author mentioned, although the associations were high at both sites, Phenocam-derived data will be affected by the heterogeneous nature.

However, the restrictions of digital photos can directly influence the outcome of the research. The location of the cameras should be fixed for such a long time span that it is difficult to ensure the same field of view. According to our experiment, the VIs and GPP can be not so synchronous due to the change in the illumination condition, the hue of the images and the complexity of the region.



Figure 5. Observed and Predicted NDVI using GCC and Exposure Time (blue, observed; red, predicted)

4.2. Other Potential Risk Factors

4.2.1. Illumination.

We observed that the extracted VIs correlated significantly with the illumination conditions. The VIs increased with stronger incoming daylight and decreased with weaker daylight. On cloudy days, the gloomy weather largely weakened the illumination due to less incoming sunlight. Moreover, the hues displayed on the images were shifted from bright colors to dim and dark ones. These resulted in consequences that some of the days generated extremely low VIs, which had no relationships with the conditions of the mangrove forests. The same situation can be applied to rainy days, which were usually accompanied by clouds. It was noteworthy that on rainy days, large rain droplets may descent on the lens of the cameras. These stains were also potential causes of sudden decreases in VIs. In this paper, we adopted the method from Herrera-Silveira [17] and only extracted VIs from images captured from 10 am to 2 pm when the daylight is relatively stable. Results showed that this method helped control the effects of illumination change.

4.2.2. Effects of Different Time-Smoothing Methods.

The moving mean smoothing method generates similar results compared to the moving median smoothing method, while the moving 90% quantile smoothing method could minimize the fluctuations caused by weather changes and other potential factors. The moving mean smoothing method can be affected by extreme values, which has appeared relatively frequently in our research. The moving 90%

quantile smoothing method may be inaccurate because it only displays the pattern of data with large values and so that ignores comparatively small ones.

5. Conclusion

This study demonstrates that camera-based indices can be used to model phenology in mangrove ecosystems. Although some limitations still need to be addressed, like poor illumination and camera shifts, the approach presented in the paper provides a simple and cost-effective way to monitor and predict mangrove growth. Given the vital role of mangrove trees in mitigating global warming, a useful quantification of mangrove phenology can help us understand better how mangroves are responding to the climate change, and thus make more sound conservation strategies.

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