Species Classification and Carbon Stock Assessment of Mangroves in Qi’ao Island with Worldview-3 Imagery

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Abstract: Mangroves play a substantial role in the global carbon cycle and are highly productive. To evaluate the effectiveness of a remote-sensing image in mangrove-species classification and carbon stock assessment, we utilized Worldview-3 images to map the mangrove species in Qi’ao Island, Guangdong Province, China, using a Random Forest classifier. We compared the contribution of spectral features, derivation features, and textural features to the classification accuracy and found that textural features significantly improved the overall accuracy, achieving 92.44% with all features combined. According to field-survey results, the main mangrove species in Qi’ao Island were Sonneratia apetala (SA), Acanthus ilicifolius (AI), Kandelia candel (KC), Acrostichum aureum (AA), Aegiceras corniculatum (AC), and Heritiera littoralis (HL); there are also many reeds mixed with mangroves. According to classification results, the total area of the mangroves and reeds is about 451.86 ha; the SA was the dominant species with an area of 393.90 ha. We calculated the total carbon stock of mangroves on Qi’ao Island by integrating the area of different species and their average total carbon density for the first time. The total carbon stock of mangroves in Qi’ao Island is between 147.78–156.14 kt, which demonstrates the significant potential of mangroves in carbon sequestration.

Keywords: mangrove; spectral features; textual features; Worldview-3 image; species classification; carbon storage

1. Introduction

Mangroves are woody halophytes that grow in tropical and subtropical intertidal zones [1]. As one of the most productive wetland ecosystems on earth, it is essential for biodiversity’s conservation and for wetland’s ecological protection in the world [2]. In addition, mangroves play a critical role in coastal protection, their root systems stabilizing sediments and effectively reducing erosion from storms and waves [3]. At the same time, they serve as important hotspots for marine biodiversity, providing habitat and breeding grounds for a wide variety of species, including fish, birds, and shellfish [4,5]. They also help maintain the quality of coastal waters by filtering and absorbing nutrients and pollutants from terrestrial sources [6]. More importantly, mangroves have high carbon-sink potential and play important roles in maintaining the global carbon cycle. Studies have shown that mangroves sequester 5% of the carbon in the atmosphere using only 0.1% of the earth surface area [4].

Globally, the research on mangroves encompasses a spectrum of themes including conservation, restoration, and ecological function. In the biodiversity-rich region of Southeast Asia, the focus frequently gravitates towards community-based conservation and the sustainable use of these ecosystems [7–10]. In addition, socio-economic evaluations of mangroves gain
prominence in regions like India and Bangladesh, where the livelihoods of local communities are inextricably linked with these ecosystems [11–13]. In countries such as Australia and China, the focus is often on understanding the impact of human activities on mangroves and developing appropriate conservation and management strategies [6,14–16]. Furthermore, there is growing global interest in understanding the ecological role of mangroves, particularly in carbon cycling and climate adaptation [17,18].

Currently, the carbon-storage capacity of mangrove ecosystems is under threat from multiple fronts. Research has shown that excessive development, pollution, and deforestation are severely threatening the survival of mangroves, activities that not only reduce their cover, but also disrupt their natural ecological balance, thereby impacting their ability to sequester carbon [3]. The accumulation of heavy metals in mangrove root systems adversely affects the number of leaves and biomass, and even reduces photosynthetic rates [19]. In addition, herbicides cause mangrove leaves to yellow and wilt, inhibiting their photosynthetic processes [20]. Exposure of mangroves to acid rain reduces the ratio of chlorophyll a to b, further affecting photosynthesis [21]. Of note is the effect of high atmospheric ozone concentrations caused by climate change, which inhibits plant growth, reduces leaf productivity, and decreases photosynthetic rates—a phenomenon also observed in mangroves [22–24]. Considering these factors, a thorough understanding and assessment of mangroves as critical carbon sinks has become imperative. Only through accurate and rapid methods for estimating the total carbon-storage capacity of mangroves can we effectively assess their contribution to the global carbon cycle, while identifying the threats and challenges they face. This process is not only important for scientific research, but also provides governments with critical information to formulate plans [25,26].

However, the majority of mangrove communities are mixed, with varying carbon densities and carbon stocks among different species [27–29]. In order to accurately estimate the total carbon stock encompassing the entire mangrove area, it is imperative to meticulously account for the contribution of each individual species. Thus, conducting a comprehensive survey to detect the distribution structure of different mangrove species within a given community is an essential prerequisite.

Due to the mangroves’ growth in intertidal zones, the muddy environment makes conventional surveys challenging in terms of precise location and accurate extraction of mangrove-community-distribution information [30]. Furthermore, such surveys are both time-consuming and cost-prohibitive. Remote-sensing technology, characterized by its extensive coverage and lower cost of data acquisition compared to field surveys, has been widely employed for detecting the distribution of mangroves and monitoring their changes, with multispectral remote images such as SPOT [31], Landsat [32], and Sentinel-2 [33] playing a prominent role in this endeavor. However, in small areas of mangrove growth, such as Qi’ao Island, located in the Guangdong Province, China, the growth zones of different mangrove species vary in size and are widely dispersed. Utilizing low- to median-resolution imagery in such context may only allow for the differentiation between mangrove and non-mangrove land cover, thus presenting challenges in achieving different species at the community level [34]. With the enhancement of spatial resolution, satellite images offer increased spatial and textural information, thereby enabling the application of multispectral data for classifying mangrove species in small-scale areas. Wang et al. [34] assessed the classification capability of the 0.5 m resolution Pléiades-1 satellite images for the identification of artificial mangrove species and found that four major artificial mangrove species could be effectively recognized. In addition, Rahmandhana et al. [35] mapped mangrove species within the Karimunjawa National Park in Indonesia based on WorldView-2 Imagery.

Despite the widespread use of high-resolution multispectral satellite imagery, several challenges persist in the field of mangrove-species identification. The main problem is the minimal variation in spectral reflectance between some mangrove communities, which makes them easy to confuse [30]. Additionally, small, patchy mangrove communities growing in the vicinity of dominant species are prone to misclassification [36]. To address
these challenges, some researchers have turned to combining high-resolution multispectral satellite imagery with Unmanned Aerial Vehicle (UAV), light detection and ranging (LiDAR) data to enhance classification accuracy [37–39]. However, this approach undoubtedly necessitates a greater number of resources, thereby increasing the research’s overall cost and demands. The WorldView-3 satellite offers a promising solution as it is equipped with a sensor that has eight multi-spectral bands and one panchromatic band with a high spatial resolution of 0.31 m [40]. With more bands and higher resolution, WorldView-3 is at the forefront of commercial-satellite technology. This offers significant potential for accurate classification of mangrove species from a single data source. However, our current understanding of the effectiveness of WorldView-3 satellite data in mangrove-species classification remains somewhat limited. Comprehensive research on the practical performance of its spectral, textural, and differential spectral characteristics in identifying mangroves in small areas such as Qi’ao Island has yet to be conducted. Additionally, the interactions between different feature combinations have not been fully considered. Consequently, further research is warranted to delve deeper into the application and optimization of these critical features, ultimately enhancing the accuracy and reliability of mangrove-species classification.

Hence, to address the above issue, this study, using Qi’ao Island as a case study, investigates the effects of different feature combinations extracted from WorldView-3 imagery on mangrove-species classification, aiming to identify the optimal combination. Subsequently, this optimal combination is used in the study for the identification of mangrove species, followed by the estimation of the total carbon stock in the mangroves of Qi’ao Island by combining the field survey data.

2. Study Area and Data Materials
2.1. Study Area
Qi’ao Island (113°36’ E–113°40’ E, 22°22’ N–113°27’ N) is in the northeast of Zhuhai, Guangdong province, China (Figure 1). The mangroves are mainly centralized in its west and northwest region. The mangrove wetland in Qi’ao Island has been listed as one of the most important wetlands in China, and it has been set as a nature reserve of Guangdong province. This region has a subtropical monsoon climate, with high temperatures and abundant rainfall all year round. The annual average temperature is 22 °C; the average precipitation is 1700 mm [41].

Figure 1. Location of the Qi’ao Island, Guangdong Province, China, and Worldview-3 image covering Qi’ao Island.
More than twenty species of mangroves have been reported in this area, and the dominant species include Sonneratia apetala (SA), Acanthus ilicifolius (AI), Kandelia candel (KC), Acrostichum aureum (AA), and Aegiceras corniculatum (AC); there are also a few semi-mangrove species, such as Heritiera littoralis (HL). In addition, numerous reeds (RE) are associated with the mangrove growth region [42,43].

2.2. Satellite Data and Pre-Processing

In this study, WorldView-3 is used to distinguish different mangrove species. WorldView-3 is a fourth-generation high-spatial-resolution optical satellite operated by the American company Digital Globe, which launched on 13 August 2014. With an image-resolution capability of 0.31 m, WorldView-3 is the highest spatial resolution optical satellite available for civilian use. It can also provide 8-band multi-spectral imagery with 1.24 m resolution, 8-band shortwave infrared imagery with 3.7 m resolution, and 12-band CAVIS with 30 m resolution. Because of this range of spectral coverage and near-infrared and shortwave-infrared capabilities, WorldView-3 images have been used for a variety of purposes, including monitoring of mineral exploration, vegetation, coastal monitoring, and other broad applications [44].

A WorldView-3 L1-level image covering the entirety of the Qi’ao Island, which was acquired on 15 January 2018, was collected, it contains one panchromatic band and eight multi-spectral bands ranging from 400 to 1040 nm. The panchromatic band was resampled to 0.5 m and multi-spectral bands were resampled to 2 m for the reason of confidentiality. The collected image was first created using the FLAASH Atmospheric Correction and Gram-Schmidt Pan Sharpening in ENVI 5.3 software, and then the fused image was generated from a panchromatic band and multi-spectral bands with the spatial resolution of 0.5 m.

2.3. Field Data

The field investigation was conducted in May 2018. Due to the limitation of image resolution, it is difficult to label small-mangrove species as samples from the WorldView-3 image accurately, and obtaining close-up photos with location information is very important. A DGPS (Differential Global Positioning System) was used to record the geographical location of field-sampling pictures, which were captured from ground with a digital camera. A DJI phantom 4 (DJI, Shenzhen, China) UAV (unmanned aerial vehicle) was used to take photos of mangrove samples in areas that are difficult for humans to reach at low altitudes. UAV photos also contain the accurate geographical location, which can accurately reflect the location of mangrove samples (Figure 2). These pictures were used to establish interpretation keys for the identification of mangroves species, while the positions were used to link sample pictures with corresponding pixels in the WorldView-3 image.

<table>
<thead>
<tr>
<th>Species</th>
<th>SA</th>
<th>AI</th>
<th>AA</th>
<th>KC</th>
<th>AC</th>
<th>HL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground pictures</td>
<td><img src="path" alt="Image" /></td>
<td><img src="path" alt="Image" /></td>
<td><img src="path" alt="Image" /></td>
<td><img src="path" alt="Image" /></td>
<td><img src="path" alt="Image" /></td>
<td><img src="path" alt="Image" /></td>
</tr>
<tr>
<td>UAV pictures</td>
<td><img src="path" alt="Image" /></td>
<td><img src="path" alt="Image" /></td>
<td><img src="path" alt="Image" /></td>
<td><img src="path" alt="Image" /></td>
<td><img src="path" alt="Image" /></td>
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</tr>
</tbody>
</table>

**Figure 2.** Sampling pictures of different mangrove species captured with a digital camera and UAV in Qi’ao Island.
2.4. Mangrove Carbon-Density Data

To estimate mangrove carbon stocks in the study area, we collected data on the carbon density of mangrove species in the corresponding area. Hu et al. [45] carried out an investigation of different restoration species to assess carbon density in Qi’ao Island, and several representative sample plots of different mangrove species were selected for the measurement of carbon density in his investigation, including vegetation carbon density (VCD), soil carbon density (SCD), and litter carbon density (LCD), which together form the total carbon density (TCD) of each species. VCD was estimated using an allometric growth equation by recording tree height and diameter at breast height of different mangrove species; SCD was determined by sampling the soil and using an element analyzer; and LCD was measured by collecting litter within the sample plot. The results are shown in Table 1. Notably, SA has the highest TCD, while Sporobolus alterniflora (SA2) has the lowest TCD. With these carbon-density data, the carbon stock of the entire Qi’ao Island mangrove ecosystem can be estimated on the basis of mangrove-species classification.

Table 1. Carbon density of different mangrove species in Qi’ao Island [45].

<table>
<thead>
<tr>
<th>Species</th>
<th>VCD/(t·ha) ± SE</th>
<th>SCD/(t·ha) ± SE</th>
<th>LCD/(t·ha) ± SE</th>
<th>TCD/(t·ha) ± SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA</td>
<td>159.99 ± 12.12</td>
<td>196.72 ± 9.85</td>
<td>1.48 ± 0.13</td>
<td>356.92 ± 5.72</td>
</tr>
<tr>
<td>KC</td>
<td>63.50 ± 2.25</td>
<td>190.48 ± 8.95</td>
<td>0.56 ± 0.07</td>
<td>267.35 ± 7.85</td>
</tr>
<tr>
<td>AA</td>
<td>0.79 ± 0.02</td>
<td>190.88 ± 7.23</td>
<td>0.41 ± 0.02</td>
<td>192.08 ± 7.26</td>
</tr>
<tr>
<td>AI</td>
<td>1.13 ± 0.02</td>
<td>165.34 ± 8.12</td>
<td>0.24 ± 0.03</td>
<td>166.72 ± 8.13</td>
</tr>
<tr>
<td>AC</td>
<td>40.49 ± 0.53</td>
<td>155.86 ± 9.19</td>
<td>0.54 ± 0.04</td>
<td>196.91 ± 9.50</td>
</tr>
<tr>
<td>HL</td>
<td>69.40 ± 2.57</td>
<td>200.46 ± 5.12</td>
<td>1.83 ± 0.15</td>
<td>270.60 ± 4.73</td>
</tr>
<tr>
<td>SA2</td>
<td>1.47 ± 0.00</td>
<td>113.55 ± 7.83</td>
<td>0.01 ± 0.00</td>
<td>115.03 ± 7.83</td>
</tr>
</tbody>
</table>

3. Methods

Through pre-processing the Worldview-3 image and calculating index features, first derivative features and texture features, the spectral bands of the Worldview-3 image are combined with all of the above features, and field data and Random Forest classification methods are used for mangrove-species classification. The area of different mangrove species in Qi’ao Island is extracted, and the TCD of Qi’ao Mangrove Reserve is calculated according to the carbon density of different mangrove species. The technical route is described in Figure 3.

3.1. Selection of Samples

A total of 520 samples were selected with 2 m × 2 m rectangles from the mangrove-distribution area, referring to the GPS position and UAV pictures. There are eight types of land cover in the samples, including five types of mangrove species (SA, KC, AA, AI, AC), one type of semi-mangrove species (HL), reeds (RE), and non-vegetation (NV), which was merged with mudflat and water. The samples were divided into training samples and validation samples at a ratio of 1:1; the training samples were used as input to train the Random Forest models, and the validation samples were applied to validate the performance of the models. Details about the samples are shown in Table 2, and the average spectral reflectance of samples are plotted in Figure 4.

Table 2. Samples for species classification.

<table>
<thead>
<tr>
<th></th>
<th>SA</th>
<th>KC</th>
<th>AA</th>
<th>AI</th>
<th>AC</th>
<th>HL</th>
<th>RE</th>
<th>NV</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training samples</td>
<td>55</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>20</td>
<td>25</td>
<td>35</td>
<td>35</td>
<td>260</td>
</tr>
<tr>
<td>Validation samples</td>
<td>55</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>20</td>
<td>25</td>
<td>35</td>
<td>35</td>
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Figure 3. Methodology flow chart.

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Table 2. Samples for species classification.

<table>
<thead>
<tr>
<th>Species</th>
<th>Training samples</th>
<th>Validation samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>KC</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>AA</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>AI</td>
<td>30</td>
<td>30</td>
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<tr>
<td>AC</td>
<td>20</td>
<td>25</td>
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<tr>
<td>HL</td>
<td>25</td>
<td>35</td>
</tr>
<tr>
<td>RE</td>
<td>35</td>
<td>35</td>
</tr>
<tr>
<td>NV</td>
<td>260</td>
<td>260</td>
</tr>
</tbody>
</table>

Figure 4. Average spectral curves of different mangrove species.
3.2. Extraction of the Features

To obtain accurate classification of mangrove species, several features calculated from WorldView-3 were used as important parameters for Random Forest models. Details are described as follows.

3.2.1. Index Features

Several indices such as the Normalized Difference Vegetation Index, Normalized Difference Water Index, Enhanced Vegetation Index, and Difference Vegetation Index were applied in the extraction of each land-cover type. These indices are generally calculated with the bands that can characterize the spectral features of vegetation, water, or soil. Different mangrove species may present great differences between these indices; they were accordingly employed as input parameters for classification in this study, and expression of them are shown in Table 3.

Table 3. Index features of Worldview-3 Imagery.

<table>
<thead>
<tr>
<th>Index Features</th>
<th>Formulation</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normalized Difference Water Index</td>
<td>Blue–NIR - (NIR + Red)</td>
<td>[46]</td>
</tr>
<tr>
<td>Normalized Difference Vegetation Index</td>
<td>NIR–Red - (NIR + Red)</td>
<td>[47]</td>
</tr>
<tr>
<td>Enhanced Vegetation Index</td>
<td>$2.5 \times \frac{NIR - 6 \times Red - 7.5 \times Blue + 1}{NIR - Red}$</td>
<td>[48]</td>
</tr>
<tr>
<td>Difference Vegetation Index</td>
<td>$\frac{k(\lambda_i) - k(\lambda_{i-1})}{\lambda_{i+1} - \lambda_{i-1}}$</td>
<td>[49]</td>
</tr>
</tbody>
</table>

3.2.2. Derivation Features

In order to better highlight the spectral differences between different classified objects, we calculated the derivative of the spectral curve [50]. The derivative of the spectral curve, or its mathematical function, estimates the slope of the entire interval [51]. In general, the first-degree derivative is more widely used in the identification of plant spectral features, and in the correlation analysis of spectral information and vegetation information [52]. The first-degree deviation is expressed as follows:

$$k(\lambda_i) = \frac{k(\lambda_{i+1}) - k(\lambda_{i-1})}{\lambda_{i+1} - \lambda_{i-1}},$$

where $\lambda_{i-1}$, $\lambda_i$, and $\lambda_{i+1}$ is the wavelength at the $i-1$-th, $i$-th, and $i+1$-th band, respectively, $k(\lambda_{i-1})$, $k(\lambda_i)$, and $k(\lambda_{i+1})$ is the reflectance at the $i-1$-th, $i$-th band, and $i+1$-th, respectively.

The first-degree deviation of original spectral reflectance was calculated, and the deviation curves of training samples are shown in Figure 5. Comparing Figures 4 and 5, it can be found that the spectral distinguishability between different mangrove species is obviously improved.

3.2.3. Textural Features

However, mangrove species cannot yet be entirely distinguished with first-degree deviation and spectral indices due to the similar spectral responses between them. It has proven that textural features can provide abundant spatial details and are usually beneficial for the identification of vegetation targets in high-spatial-resolution images [53]. It is necessary to induce textural information for more accurate classification of mangrove species. The Grey Level Co-occurrence Matrix [47] has been widely used and proven to be helpful in many research cases [54]. The main eight features including mean, variance, homogeneity, contrast, dissimilarity, entropy, angular second moment, and correlation can be obtained from the Grey Level Co-occurrence Matrix, and expressions of these features are shown in Table 4.
Figure 5. First-degree derivation of reflectance of different mangrove species.

Table 4. Textural features of Grey Level Co-occurrence Matrix.

<table>
<thead>
<tr>
<th>Textural Features</th>
<th>Formulation</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>[ u_i = \sum \sum i \cdot P[i,j] ]</td>
<td>[55]</td>
</tr>
<tr>
<td>Variance</td>
<td>[ \sum \sum (i - u_i)^2 \cdot P[i,j] ]</td>
<td>[56]</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>[ \sum \sum \frac{P[i,j]}{i+1(i+j)} ]</td>
<td>[50]</td>
</tr>
<tr>
<td>Contrast</td>
<td>[ \sum \sum P[i,j] - \sum P[i,j] ]</td>
<td>[50]</td>
</tr>
<tr>
<td>Dissimilarity</td>
<td>[ \sum \sum i \cdot P[i,j] ]</td>
<td>[55]</td>
</tr>
<tr>
<td>Entropy</td>
<td>[ \sum \sum P[i,j] \ln P[i,j] ]</td>
<td>[50]</td>
</tr>
<tr>
<td>Angular Second Moment</td>
<td>[ \sum \sum P[i,j]^2 ]</td>
<td>[57]</td>
</tr>
<tr>
<td>Correlation</td>
<td>[ \frac{\sum \sum i \cdot P[i,j] - u_i u_j}{\sigma_i \sigma_j} ]</td>
<td>[55]</td>
</tr>
</tbody>
</table>

Note: \( i \) is the row number of the image; \( j \) is the column number of the image; \( P[i,j] \) represents the relative frequency of two neighboring pixels. \( \sigma_i \) and \( \sigma_j \) are the standard deviation of values for \( i \) and \( j \)’s references.

Above, eight texture features were calculated using the red band (Band 5) [58] of WorldView-3 with the windows of \( 5 \times 5, 7 \times 7, 9 \times 9 \), etc., until the highest classification accuracy was achieved.

3.2.4. Features Combinations

To explore the potential of the WorldView-3 image in mapping different mangrove species, five combinations of above features were tested to evaluate their relative effectiveness (Table 5). The original spectral values of a WorldView-3 image were used as the basic features, with which the index features, derivation features, and textural features were combined. Finally, we combined all the features to discover their ability for species classification.
3.3. Random Forest Classifier

The Random Forest algorithm, initially proposed by Bierman [59], is a classifier that consists of multiple independent decision trees to classify and predict randomly selected sample information. It utilizes a ‘bootstrap aggregating’ or ‘bagging’ method to create the training set for each decision tree, and then integrates multiple decision trees to obtain the predicted results through voting [60,61]. With the advantages of being insensitive to parameters, difficult to overfit, having fast training and good performance in interspecific classification, the Random Forest classifier has been successfully applied in the classification of mangroves [62,63]. In this study, we employed the Random Forest classifier with consistent parameters for various feature combinations.

3.4. Accuracy Assessment

To represent the accuracy of the classification, the most commonly used is a Confusion Matrix, which is utilized to look into the class confusion between various mangrove species. Four indices including the overall accuracy (OA), the kappa coefficient (Kappa), the producer’s accuracy (PA), and user’s accuracy (UA) were calculated to evaluate the mangrove-species classification. Therein, OA refers to the proportion of correctly classified pixels. While OA can effectively represent the accuracy of classification, it is highly influenced by the large number of pixel categories for multi-category ground objects with an extremely imbalanced number of category pixels, which cannot well represent the classification accuracy of each category. The kappa coefficient represents the proportion of error reduction between classification and random classification with complete data, and it is commonly used to assess the consistency between classification outcomes and reference data. Regarding one type, PA indicates the proportion of correctly classified pixels to the total samples, while UA indicates the proportion of the correctly classified pixels to the total pixels classified into this category. The formulas is as follows:

\[
OA = \frac{\sum_{k=0}^{n} T_k}{N}
\]

\[
PA = \frac{\sum_{k=0}^{n} T_k}{\sum_{k=0}^{n} R_k}
\]

\[
UA = \frac{\sum_{k=0}^{n} T_k}{\sum_{k=0}^{n} P_k}
\]

\[
Kappa = \frac{OA - P_e}{1 - P_e}
\]

\[
P_e = \frac{\sum_{k=0}^{n} R_k P_k}{N^2}
\]

where \(n\) is the number of species, \(N\) is the total number of validation samples, \(T_k\) is the number of samples correctly classified as species \(k\), \(R_k\) is the number of validation samples of species \(k\), and \(P_k\) is the number of samples classified as species \(k\).
3.5. Mangrove Carbon-Stock Assessment

To estimate the total carbon stock of mangrove in Qi’ao Island, representative mangrove sample plots were selected to calculate carbon-density data. Total carbon stock (TCS) was calculated with the carbon-density data and area of mangrove species, which were obtained from the classification results. It can be expressed as the following equation:

\[ TCS = \sum_{k=0}^{n} D_k S_k \]  

(7)

where TCS refers to the total carbon stock, \( n \) refers to the total types of mangrove species and reeds, \( D_k \) refers to the TCD of the \( k \)th mangrove species, \( S_k \) refers to the area of the \( k \)th mangrove species, \( U_{TCS} \) refers to the uncertainties of total carbon stock, and \( U_k \) refers to the TCD uncertainties of the \( k \)th mangrove species.

4. Results and Analysis

4.1. Accuracy Assessment of the Mangrove-Species Classification

Mangrove species were classified using a Random Forest classifier in ENVI 5.3 software with the different combinations of Worldview-3 Imagery in Table 5 using the same training samples in Table 2. The same validation samples in Table 3 were used to evaluate the accuracy of the classified results, the accuracy validation is shown in Table 6 and Figure 6, and the confusion matrix is shown in Tables S1–S5.

Table 6. Classification accuracy of Worldview-3 Imagery and features.

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Input Features</th>
<th>OA</th>
<th>Kappa</th>
<th>Confusion Matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Original Spectral Values</td>
<td>77.20%</td>
<td>0.6753</td>
<td>Table S1</td>
</tr>
<tr>
<td>S2</td>
<td>Original Spectral Values and Index Features</td>
<td>78.81%</td>
<td>0.6987</td>
<td>Table S2</td>
</tr>
<tr>
<td>S3</td>
<td>Original Spectral Values and Derivation Features</td>
<td>81.21%</td>
<td>0.7373</td>
<td>Table S3</td>
</tr>
<tr>
<td>S4</td>
<td>Original Spectral Values and Textural Features</td>
<td>89.53%</td>
<td>0.8577</td>
<td>Table S4</td>
</tr>
<tr>
<td>S5</td>
<td>Original Spectral Values and All Features</td>
<td>92.44%</td>
<td>0.8972</td>
<td>Table S5</td>
</tr>
</tbody>
</table>

Figure 6. Producer’s accuracy and user’s accuracy of mangrove species with different feature combinations.

Table 6 and Figure 6 demonstrate that the original spectral values of the Worldview-3 image achieved an OA of only 77.20% due to the similarity of spectral features among various mangrove species shown in Figure 4. Index features did not significantly improve the OA, while first-degree deviation of the spectrum played a significant role in improving it. Textual features greatly improved the classification performance, resulting in an OA increase of 12.33%. The experimental results (Figure 7) show that when the window size
Figure 7. Overall accuracy improvement using textual features.

Figure 6 illustrates that the producer’s accuracy and user’s accuracy of NV can consistently achieve high accuracy, even when feature data is not included. This is largely due to the distinct spectral features of NV compared to those of the mangrove species or vegetation. From Table S1, the accuracy of AC was the lowest, with a producer’s accuracy of 8% and a user’s accuracy of 18.18%. The similarity in spectral reflectance led to misclassifications between AC, AA, and RE, as well as between SA, KC, HL, and RE [36]. Table S2 reveals that even after incorporating spectral index features into the classification process, the accuracy of AC and RE remained low. Table S3 indicates that the first-order derivative of spectral bands improved the classification accuracy of HL by 25.28% and RE by 12.51%. This was due to the differences in the first-derivative features between SA, HL, and RE. Table S4 reveals that the combination of textural and spectral features significantly improved the overall classification accuracy, with AC being well distinguished by an improvement of 84.80% in producer’s accuracy and 52.77% in user’s accuracy. When all features were combined into a Random Forest classifier, further improvements in accuracy could be achieved, as seen in Table S5.

4.2. Spatial Distribution of Mangrove Species

The classification accuracy of the original spectral values and all features was validated, and its result was transformed into a vector format for mapping the distribution of mangrove species on Qi’ao Island. This information is mapped using ArcGIS 10.2 software (Figure 8).

Mangrove species are distributed as follows: SA occupies most of the area, while NV is mainly found around water bodies and tidal flats located in the west and north of the study area or interspersed among SA. AI can be found in the southeast, middle, and south of the study area (regions A, B, and C), mixed with SA. RE or reeds grow alongside AI and are also distributed in local regions A, B, and C. The distribution of AA is relatively scattered, but it appears more frequently in region A. Finally, AA, KC, AC, and HL are mainly grown in region A. Although these mangrove species grow together in a mixed community, the distribution of the same species is relatively concentrated. According to on-site investigations, there is a high concentration of AI, RE, and AA below the crown layer in SA. Due to the limitations of visible-light remote-sensing images, AI, RE, and AA located below the AA crown layer cannot be accurately mapped.

Figure 8. Overall Accuracy 72%, 74%, 76%, 78%, 80%, 82%, 84%, 86%, 88%, 90%, 92%

<table>
<thead>
<tr>
<th>Window size</th>
<th>Overall Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>5×5</td>
<td>72.00%</td>
</tr>
<tr>
<td>7×7</td>
<td>74.20%</td>
</tr>
<tr>
<td>9×9</td>
<td>76.40%</td>
</tr>
<tr>
<td>11×11</td>
<td>78.60%</td>
</tr>
<tr>
<td>13×13</td>
<td>80.80%</td>
</tr>
<tr>
<td>15×15</td>
<td>83.00%</td>
</tr>
<tr>
<td>17×17</td>
<td>85.20%</td>
</tr>
<tr>
<td>19×19</td>
<td>87.40%</td>
</tr>
<tr>
<td>21×21</td>
<td>89.60%</td>
</tr>
</tbody>
</table>

is set at 19 × 19, the improvement in OA reaches its maximum value. Based on this feature combination, we added all features to the original spectral values, and the resulting classification accuracy was consistent with expectations.
Figure 8. Spatial distribution of mangrove species in Qi’ao Island.

4.3. Area and Carbon Stock Assessment

The classification result of original spectral values and all features was mapped onto the Universal Transverse Mercator projection in Zone 49N and Datum World Geodetic System 1984. Considering that the area covered by water bodies and tidal flats in the study area did not have any reference value for calculating carbon storage of mangroves, we conducted a statistical analysis of the area covered by all mangrove species and reeds in the study area. Based on the area statistics and the average TCD of each mangrove species listed in Table 1, we calculated carbon stock of the mangrove ecosystem on Qi’ao Island. It is worth mentioning that, Hu et al. [45] did not conduct a separate investigation on RE. In reality, RE are widely distributed and grow at the same height and in the same habitat as SA2. Therefore, we directly used the TCD of SA2 for the calculation of RE. The area and carbon stock of different mangrove species are presented in Table 7.

Table 7. Area and carbon storage of mangrove species.

<table>
<thead>
<tr>
<th></th>
<th>SA</th>
<th>KC</th>
<th>AA</th>
<th>AI</th>
<th>AC</th>
<th>HL</th>
<th>RE</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area/ha</td>
<td>393.90</td>
<td>16.58</td>
<td>5.58</td>
<td>7.90</td>
<td>1.04</td>
<td>8.06</td>
<td>18.80</td>
<td>451.86</td>
</tr>
<tr>
<td>Area ratio/%</td>
<td>87.17</td>
<td>3.67</td>
<td>1.24</td>
<td>1.75</td>
<td>0.23</td>
<td>1.78</td>
<td>4.16</td>
<td>100%</td>
</tr>
<tr>
<td>Average TCD/(t·ha)</td>
<td>± 5.72</td>
<td>± 7.85</td>
<td>± 7.26</td>
<td>± 8.13</td>
<td>± 9.50</td>
<td>± 4.73</td>
<td>± 7.83</td>
<td>/</td>
</tr>
<tr>
<td>Carbon stock/t</td>
<td>± 2041.58</td>
<td>± 2098.70</td>
<td>± 1394.50</td>
<td>± 1355.43</td>
<td>± 1870.65</td>
<td>± 1279.94</td>
<td>± 000.68</td>
<td>± 4182.34</td>
</tr>
<tr>
<td>Carbon ratio/%</td>
<td>92.52</td>
<td>2.92</td>
<td>0.71</td>
<td>0.87</td>
<td>0.14</td>
<td>1.43</td>
<td>1.42</td>
<td>100%</td>
</tr>
</tbody>
</table>

The total area of mangroves and reeds is about 452 ha, with SA making up 87% of the area and being the dominant species. The true mangrove area accounts for approximately 94% of the total area. The TCS of mangroves and reeds is between 147.78 and 156.14 kt
In order to validate the accuracy of area and TCS, we consulted the relevant literature on the mangrove area and carbon stock in Qi’ao Island. Sun [64] used the Geofen-2 image in 2019 to classify the mangroves on Qi’ao Island, the results showed that the pure SA forest area was approximately 332.40 ha, and the VCD of SA was approximately 55,969.24 t. The area of SA in this study is larger than Sun’s statistical results, mainly because this paper includes the area of SA mixed with other mangrove species, and, in terms of carbon stock, if we only consider the VCD of vegetation, the carbon storage value of SA in this paper is close to Sun’s research result. The VCD of SA in Sun’s paper was 168.38 t/ha and this paper uses 159.99 t/ha, so the difference is not large.

5. Discussion

Historically, field investigations within mangrove ecosystems were predominantly confined to marginal areas, as the inaccessibility of denser mangrove regions posed significant challenges to on-foot exploration. In addition, it was tricky to document in the field. In the study, the use of UAV allowed us to collect more information on mangroves on a larger scale, and the use of UAV imagery allowed for the precise selection of training and validation samples of satellite imagery, thereby increasing the accuracy of satellite-image classification, while minimizing or eliminating the interference of field surveys in mangrove ecosystems [65]. Islam et al. [40] corroborated that UAV-derived information was effective in mapping wet vegetation. Research by Oldeland et al. has shown that UAV can greatly assist field surveys for plant-species monitoring by providing accurate species maps as well [66]. Thus, in the future, UAV could be used to assist in the investigation of all types of field studies of plants, not just mangroves.

Based on WorldView-3 imagery, we investigated the effects of different feature combinations on the classification accuracy of mangrove species. The findings demonstrated a significant improvement in classification accuracy due to the incorporation of texture features. This improvement was attributed to the inherent variation among the different species within the mangrove ecosystem, which included a variety of leaf shapes, average heights, and branch structures [40]. In high-resolution remotely sensed imagery, these distinct attributes appear as texture features [50]. Especially for images with detailed structure, texture features can significantly improve classification accuracy [67,68]. Kwak and Park [69] demonstrated that the utilization of texture features significantly enhanced the classification proficiency of the Support Vector Machine classifier, and this methodology yielded a notable increment of 7.72% in overall accuracy compared to classifications relying solely on spectral information. This is similar to our results. Thus, the extraction and utilization of these distinctive texture features offer a valuable means to further enhance the accuracy of species classification. Additionally, RE also exhibited a relatively lower classification accuracy and was susceptible to confusion with other species. Research has shown that RE exhibits seasonal variations in radial reflectance, which suggests that incorporating phenological information may allow for improved differentiation from mangrove species [70,71].

In summary, WorldView-3 imagery serves as a robust basis for studying the classification of mangrove species and assessing carbon stocks. The methodology presented in this paper is versatile enough to be applied to other high-resolution remote-sensing imagery, such as GF-2 and WorldView-2, to estimate carbon stocks in a wide range of species. However, the WorldView-3 imagery, which primarily captures surface information, may miss dwarf-mangrove species that grow under taller mangrove canopies, such as AI. These nuances may affect carbon stock estimates. Future research efforts may benefit from the integration of additional remote-sensing data sources, such as LiDAR, to elucidate the three-dimensional structure of mangrove forests and ultimately improve the accuracy of species classification and carbon stock estimation [63,72].
6. Conclusions

Due to the differences in carbon sequestration rates and abilities of different mangrove species, the accurate classification of different mangrove species is crucial for estimating total carbon stock. We utilized Worldview-3 imagery to map mangrove species at the level of the individual, and, through experiments, we found that it is difficult to accurately classify multiple species of mangrove based solely on spectral features such as the index feature and first-derivative feature in remote-sensing images. However, combining texture features with spectral features can significantly improve the accuracy of inter-species classification of mangroves. Based on statistical results of mangrove area and field surveys of average TCD data for each mangrove species, this paper estimated the TCS of the entire mangrove forest on Qi’ao Island. According to the statistics, the TCS of the mangrove forest on Qi’ao Island is approximately 152 kt, with SA being the dominant species with a carbon stock of 140.6 kt. The TCS data estimated in this paper not only considers the vegetation carbon stock but also considers the litter carbon storage and soil carbon storage of the mangroves, which is often easy to overlook or difficult to achieve in mangrove carbon stock assessment. This method of carbon stock assessment has certain reference value for large-scale mangrove carbon storage estimation research.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/f14122356/s1, Table S1. Confusion Matrix of original spectral values classification data. Table S2. Confusion Matrix of original spectral values and index features classification data. Table S3. Confusion Matrix of original spectral values and derivation features classification data. Table S4. Confusion Matrix of original spectral values and textural features classification data. Table S5. Confusion Matrix of original spectral values and all feature classification data.

Author Contributions: Methodology, Y.S.; software, Z.J.; validation, M.Y., Z.J. and J.Z.; formal analysis, M.Y. and B.A.; data curation, Y.S.; writing—original draft, Y.S.; writing—review and editing, M.Y. and B.A.; supervision, Q.C.; funding acquisition, B.A. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: All data are available by contacting the corresponding author.

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

Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI</td>
<td>Acanthus ilicifolius</td>
</tr>
<tr>
<td>AA</td>
<td>Acrostichum aureum</td>
</tr>
<tr>
<td>AC</td>
<td>Aegiceras corniculatum</td>
</tr>
<tr>
<td>HL</td>
<td>Heritiera littoralis</td>
</tr>
<tr>
<td>KC</td>
<td>Kandelia candel</td>
</tr>
<tr>
<td>Kappa</td>
<td>kappa coefficient</td>
</tr>
<tr>
<td>LCD</td>
<td>litter carbon density</td>
</tr>
<tr>
<td>OA</td>
<td>overall accuracy</td>
</tr>
<tr>
<td>PA</td>
<td>producer’s accuracy</td>
</tr>
<tr>
<td>RE</td>
<td>reeds</td>
</tr>
<tr>
<td>SCD</td>
<td>soil carbon density</td>
</tr>
</tbody>
</table>
21. Cer
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