fishes

MDPI

Article

The Impact of Multiple Pond Conditions on the Performance of Dike-Pond Extraction

Jinhao Zhou [1,2,3], Wu Zhou [1], Qiqi Zhou [1], Yuanhui Zhu [4,5,*], Fei Xie [1], Shen Liang [1] and Yueming Hu [3]

[1] Department of Geoinformatic, South China Agricultural University, Guangzhou 510642, China; henryzhou541@163.com (J.Z.); zkingfire@163.com (W.Z.); z1103916922@163.com (Q.Z.); 13660918262@163.com (F.X.); shankliang@stu.scau.edu.cn (S.L.)
[2] Department of Geography, The Ohio State University, Columbus, OH 43210, USA
[3] Guangdong Provincial Key Laboratory of Land Use and Consolidation, South China Agricultural University, Guangzhou 510642, China; ymhu@scau.edu.cn
[4] School of Geographical Sciences and Remote Sensing, Guangzhou University, Guangzhou 510006, China
[5] School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ 85287, USA
* Correspondence: yzhu221@asu.edu; Tel.: +86-159-18705640

Abstract: Dike-ponds in fisheries often present multiple pond conditions such as pure, suspended sediment, water bloom, semidry conditions, etc. However, the impact of these conditions on the performance of extracting dike-pond from remote sensing images has not been studied. To solve this problem, we explore the existence of such impacts by comparing the performance of four rule-based methods in two groups of test regions. The first group has few multiple pond conditions, while the second has more. The results show that various measure values deteriorate as the proportion of multiple pond conditions in the regions increases. All four methods performed worse in the second group than the first, where the overall accuracy decreased by 8.80%, misclassification error increased by 3.69%, omission error raised by 10.53%, and correct quantity rate dropped by 8.23%, respectively. The extraction method that ingested multiple pond conditions performed indistinguishably from the other methods in the first group. However, it outperformed the other methods in the second group, with a 4.22% improvement in overall accuracy, a 10.25% decrease in misclassification error, and a 19.03% increase in the correct quantity rate. These findings suggest that multiple pond conditions can negatively impact the extraction performance and should be considered in dike-pond applications that require a precise pond size, number, and shape.

Keywords: dike-pond; classification; rule-based method; multiple pond conditions

Citation: Zhou, J.; Zhou, W.; Zhou, Q.; Zhu, Y.; Xie, F.; Liang, S.; Hu, Y. The Impact of Multiple Pond Conditions on the Performance of Dike-Pond Extraction. *Fishes* **2022**, *7*, 144. https://doi.org/10.3390/fishes7040144

Academic Editor: José Lino Costa

Received: 12 April 2022
Accepted: 17 June 2022
Published: 22 June 2022

1. Introduction

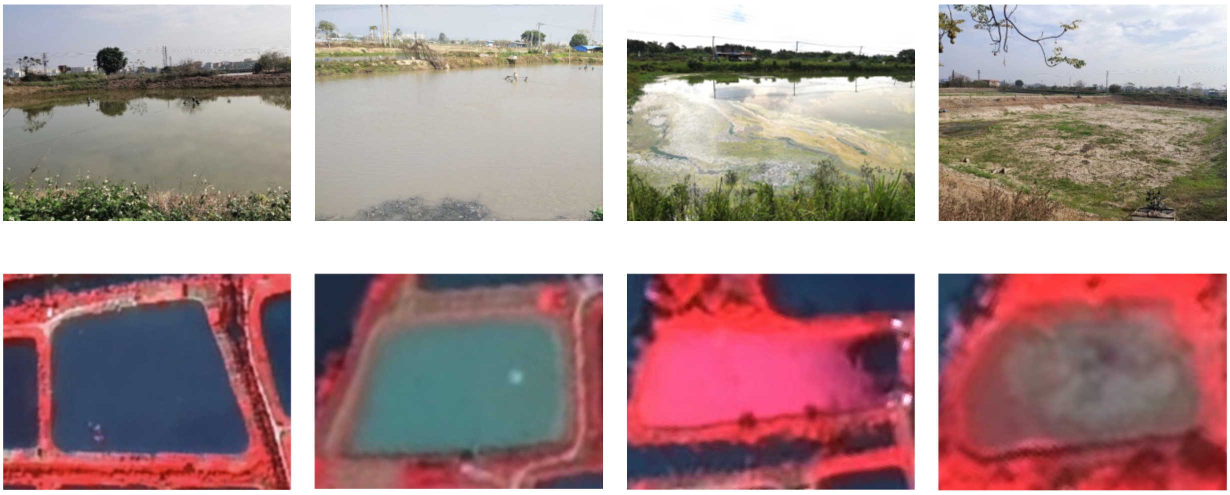
Aquaculture ponds supply essential fishery products in many countries [1–3]. A dike-pond is a particular type of aquaculture pond mainly located in the low-lying river delta of China's eastern coast [4,5]. The pond water is used for farming aquatic organisms, such as fish, shrimp, and mollusks, while the dike land is used to grow cash crops, such as vegetables, mulberries, and fruits. Due to its combination of water and land resources to adapt to the local environment [6–8], the dike-pond is designated as a globally important agricultural heritage system by the food and agriculture organization of the United Nations (FAO). Moreover, dike-pond as a type of artificial wetland benefits regional ecology, and thus is recognized as a sustainable development agriculture system [9–12]. In the last decade of rapid urban sprawl in China's eastern coastal economic zone, significant changes in the size, quantity, and pattern of dike-ponds have occurred [13,14]. These changes play an essential role in the local economic development and ecological services.

As important fishery resources, sustainable use of dike-ponds requires efficient monitoring and mapping. Conventional methods of sampling the fisheries from field investigation are limited in spatial and temporal distribution, making it difficult to examine the entire ecosystem [15]. With the development of remote sensing technologies, it has become possible to examine the extensive fishery resources in acceptable temporal-spatial resolution. For example, based on remote sensing, precise mapping of pond aquaculture can be used to estimate fishery production [16]. Chlorophyll concentrations and sea surface temperature derived from remote sensing have been used to monitor fishery resources and control fisheries [17]. Remote sensing is also applicated to identify fish distributions and abundance by satellite data-based sea surface temperature and chlorophyll-a anomalies, indicating the contribution of remote sensing to fisheries management and conservation [18]. Other applications monitor the temporal and spatial changes of fishery resources [19,20].

Remote sensing from earth observation satellites provides timely data for tracking dike-pond landscape dynamics [21–23]. There are three types of methods for extracting dike-ponds from remote sensing images. The first method is visual interpretation. The features of a dike-pond in an image (such as color, size, shape, and relationships) are visually recognized and interpreted [2,22–24]. Theoretically, this method can accurately extract dike-ponds with structure and shape details; however, the accuracies depend on the interpreter, and the method is time consuming. The second method is supervised classification. Several samples representing dike-ponds are selected from an image at first. Then, classifiers estimate which pixels or objects (groups of pixels) within the image match the features of the dike-pond samples [13,25–27]. Maximum likelihood and decision tree are the common classifiers in extracting ponds. This method has higher efficiency than visual interpretation, but the conventional classifiers encounter some difficulties, such as distinguishing dike-ponds from other classes with similar spectral features. The third method is rule-based classification. After an image is segmented into groups of neighboring homogeneous pixels (object) [16,23,28–30], a series of spectral, textural, and spatial rules are applied to identify dike-pond objects. Previous studies mainly employed rules of near-infrared (NIR) [31,32] and normalized difference water index (NDWI) [20,21,33,34]. Since these classification rules can be flexibly set and combined, in recent years, some studies have used this method to extract aquaculture ponds with Google Earth Engine expeditiously [3].

The above-mentioned methods are compatible with a single pond condition, most often the “pure” condition (Figure 1a). When pond conditions become diverse (as shown in Figure 1), this leads to substantial challenges identifying dike-ponds in multiple conditions using exiting methods. Through field investigations, it was found that ponds can become turbid during farming activities. For example, operating oxygen machines or fish foraging agitate the water and induce sediment to suspend. In addition, farmers regularly or irregularly deliver feed or medicine into ponds. These suspended sediments block sunlight from penetrating the water body, resulting in different spectral features than the pure condition (Figure 1b). Furthermore, water blooms also occur during breeding. It is the result of nutrients entering the ponds and causing excessive growth of algae. A rapid increase or accumulation in the population of algae makes the pond exhibit more vegetative features other than water (Figure 1c). Moreover, farmers drain the water after one round of breeding for cleaning purposes, at which time the pond will appear dry or semidry (Figure 1d). The different pond conditions result in a wide range of spectral features of dike-ponds. However, there is a lack of research to explore whether multiple pond conditions cause performance degradation of the extraction methods.

To fill this knowledge gap, this study aims to explore the existence of the impact of multiple pond conditions on extraction performance to help improve the extraction accuracy of dike-ponds. For this purpose, we analyze the features of various pond conditions and then compare the extraction performance between methods with and without considering multiple pond conditions. Moreover, the methods used and potential applications of this research are discussed prior to conclusions.



(**a**) Pure (**b**) Suspended sediment (**c**) Water bloom (**d**) Semidry

Figure 1. Actual scenes and corresponding images of various pond conditions.

2. Data and Methods

2.1. Data

The image used in this study was taken by the panchromatic and multi-spectral (PMS) cameras of the Chinese Gaofen-2 satellite on December 3rd, 2017. Within the spectral range of the cameras (0.45–0.90 µm), there are four spectral channels blue (B), green (G), red (R), and near-infrared (NIR). The panchromatic band has a spatial resolution of 0.8 m, and the multi-spectral bands have a spatial resolution of 3.2 m. The image has been preprocessed using systematic radiometric correction and atmospheric correction. After that, we use cubic convolution for resampling and use the NNDiffuse method for pan-sharpening.

The image has a stripe width of 23 km (22.67–22.92 N, 112.97–113.23 E) covering the center of the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) (Figure 2). This area is a delta landform created by the Pearl River, featuring dense river networks. Local farmers constructed dike-ponds in low-lying areas that are unsuitable for traditional rice farming. After hundreds of years of development, the areas have become one of the most concentrated centers of dike-ponds. The dike-ponds here have diverse pond conditions and shapes, making them ideal areas for this study.

2.2. Methods

We use two groups of regions to test the extraction performance of four methods. The first group has fewer multiple pond conditions, and the second group has more. We believe that if the extraction performance gets worse in the second group, it indicates that the impact of pond conditions needs to be seriously taken care of.

Each group has two test regions, the two regions in the first group are marked as regions #1 and #2, and another two regions in the second group are marked as regions #3 and #4. Four test regions with 1000 × 1000 pixels are selected from the image (Figure 2). Four accuracy measures (overall accuracy, misclassification error, omission error, and correct quantity rate) are computed to assess the extraction performance of the methods. The first three measures are calculated based on the confusion matrix. A confusion matrix is used to summarize the true/false pixels between the extraction results and the ground truth of the test region [35]. The fourth measure "correct quantity rate" is introduced in this study to assess the accuracy of dike-pond quantity. Such a rate is defined as the ratio of the number of correctly extracted dike-ponds to the number of actual dike-ponds based on ground truth. The value range of the correct quantity rate is 0–100%. A larger value indicates a higher correct rate.

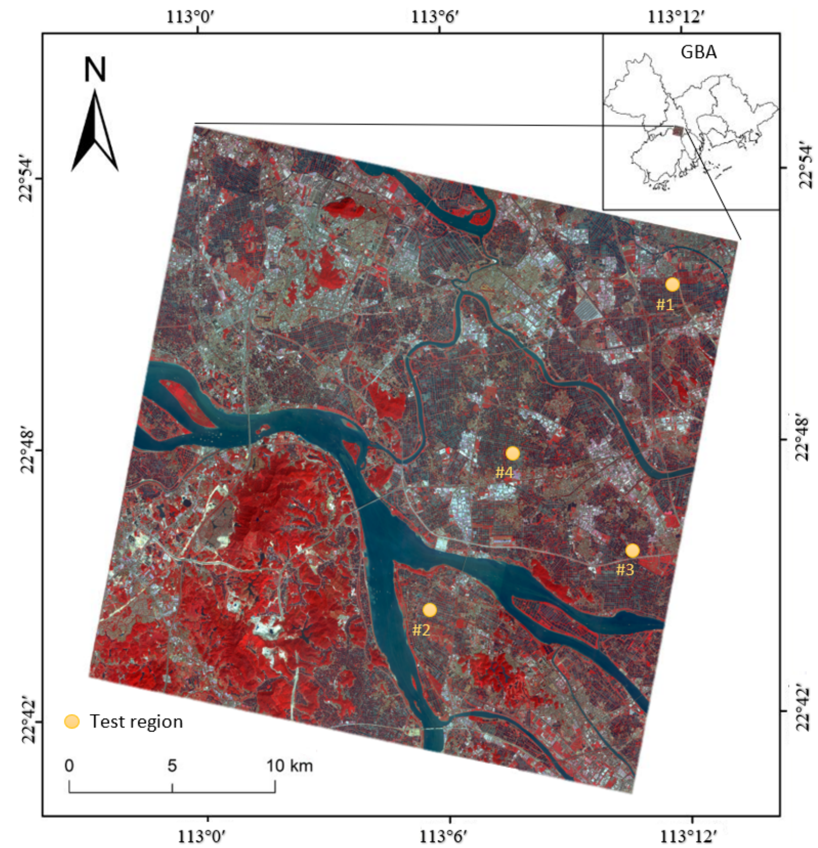


Figure 2. The Gaofen-2 image coverage area.

2.2.1. Rule-Based Methods

The four methods of dike-pond extraction compared in this study are all rule-based, marked as methods A, B, C, and D. The classification rules mainly consist of feature values or their derived indices to determine the class of each object. There are three indices that are used in four methods, including NDWI, normalized difference vegetation index (NDVI), and entropy of gray-level co-occurrence matrix (GLCM).

The NDWI is a spectral indicator that can be used to identify water bodies [36,37]. It is calculated as follows.

$$NDWI = \frac{G - NIR}{G + NIR} \tag{1}$$

where G and NIR represent the values of the green and the near-infrared band, respectively. A positive NDWI value generally indicates that the ground is covered by water.

The NDVI is a widely used indicator for assessing whether an object contains live green vegetation [38]. It is calculated as follows:

$$NDVI = \frac{NIR - R}{NIR + R} \tag{2}$$

where R and NIR represent the values of the red and near-infrared bands, respectively. The value of NDVI varies between -1 and 1, and a positive value generally indicates vegetation coverage.

The GLCM characterizes the texture by considering the spatial relationship of the pixels [39]. It determines how often pairs of pixels with specific values occur in the image.

$$P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}} \tag{3}$$

where i,j represent the row and column numbers of the matrix, respectively; N is the number of rows or columns of the matrix; $V_{i,j}$ is the value of the cell (i, j) of the matrix; and P is the normalized value of the cell. When all the values in the GLCM are equal or reach maximum randomness, the GLCM entropy is high.

We create three methods with reference to existing studies of pond extraction [3,20,31–34]. Method A uses an NDWI rule to extract water bodies, including dike-ponds, then uses shape rules (the shape index is the standardized ratio of the perimeter to the area of the object, rectangular fitting compares the area of the object to the area of the oriented bounding box enclosing the object) to exclude rivers, then NIR and GLCM rules to exclude lakes and other water bodies (Figure 3a). Method B uses NDVI and NIR rules to extract dike-ponds. A size rule with an empirical threshold is used to exclude the small water areas (Figure 3b). Method C uses an NDWI rule to identify water bodies, including dike-ponds, then uses shape rules (border ratio compares the length of the shared border between the object and another class object to the length of the object border) to exclude other water bodies (Figure 3c). The rules of these three methods are not set for multiple dike-pond conditions.

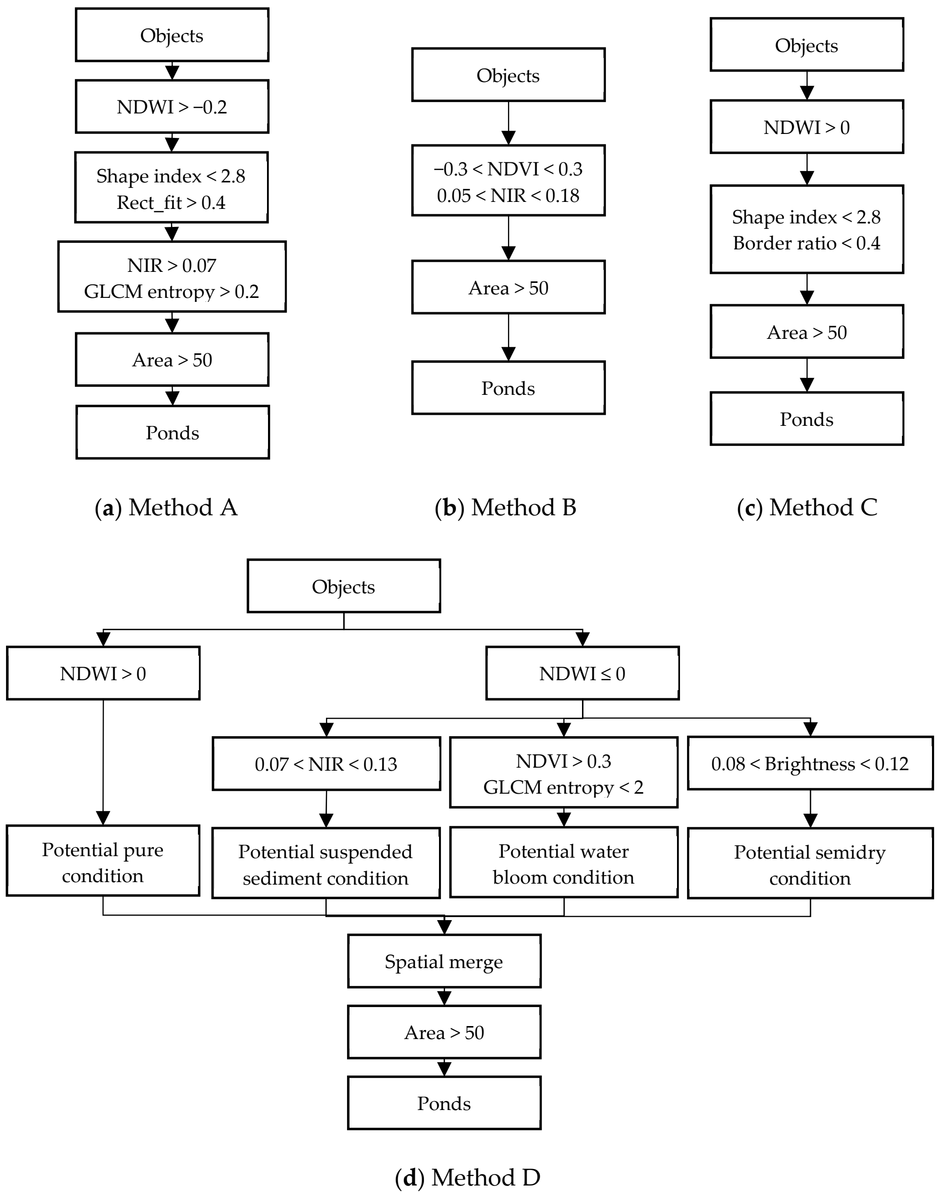


Figure 3. The classification rules of the four methods.

Method D is proposed in this study because no existing method has been developed to identify multiple pond conditions (Figure 3d). The process and indices of this method are similar to the above-mentioned three methods so they can be compared together. The rules of method D are set according to the result of feature analyses of four pond conditions, including pure, suspended sediment, water bloom, and semidry. We select 100 samples of each pond condition and statistically analyze their feature values of NIR, brightness, NDWI, NDVI, and GLCM entropy.

2.2.2. Image Segmentation

We execute object-based segmentation on the image before implementing the rule-based method. It can reduce within-class spectral variation and derive spectral, spatial, and textural information by grouping neighboring pixels together based on their homogeneity. This study applied a multi-resolution segmentation algorithm within eCognition 9.0 software (Trimble Germany GmbH, Munich, Germany).

The segmentation results vary based on a series of parameters settings. The scale parameter defines the maximum standard deviation of the homogeneity criterion. Higher values of the scale parameter result in larger objects, while lower values result in smaller objects. Color/shape and compactness/smoothness are two pairs of homogeneity criteria. The sum of each pair equals a value of one, such that they balance each other. Color is the value of an image pixel, and the shape criterion includes compactness and smoothness. Compactness is a ratio of the perimeter to the area of the object; smoothness is a perimeter ratio of the object to a minimum bounding box of the object. We set these parameters through comparative experiments. As shown in Figure 4, the scale parameter 70 presents under-segmentation results. The polygon marked in red is an object that covers more than one pond. This setting is subject to causing classification errors because each object is only assigned to one class. When the scale parameter is set to 60 or 50, the red polygon becomes smaller and covers a part of one pond, such that the two ponds are separated. The scale parameter is set to 60 in this study due to the higher classification efficiency. Similarly, the shape parameter is set to 0.10, and the color is set to 0.90. The compactness parameter is 0.50, and the smoothness is 0.50.

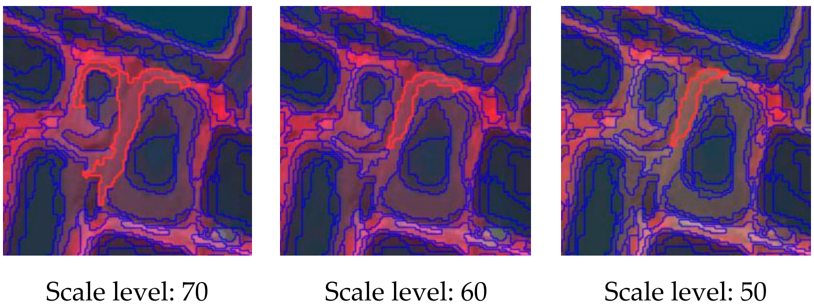
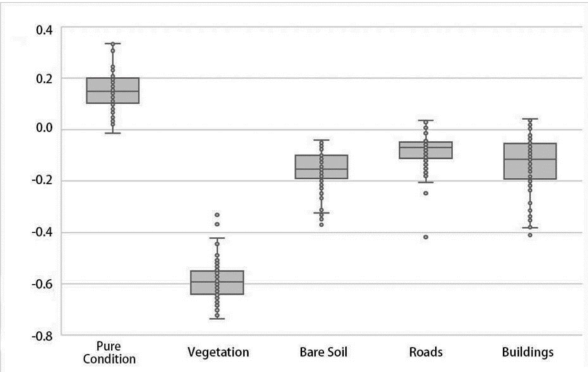


Figure 4. Segmentation results with various parameter settings.

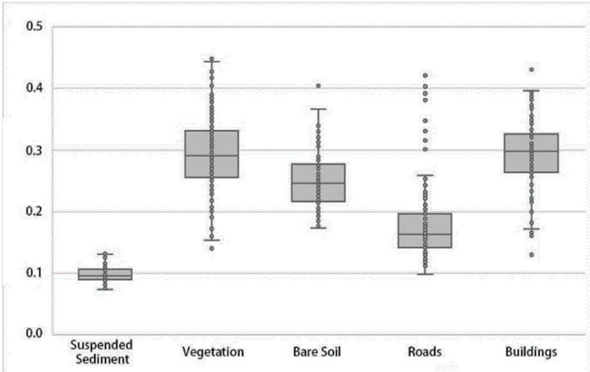
3. Results

3.1. Feature Analysis

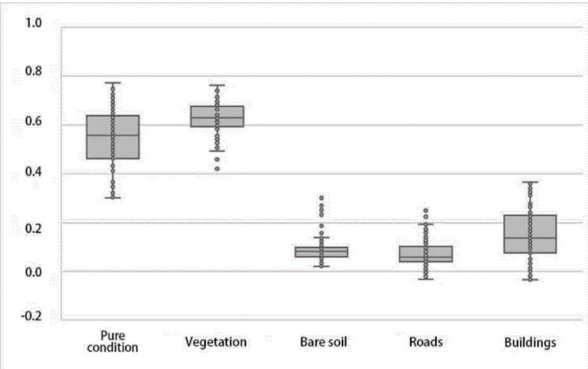
We analyze the surface reflectance values of 100 samples of four pond conditions and other object classes (e.g., vegetation, bare soil, roads, and buildings) to show the feature differences in various pond conditions. First, the pure conditions of dike-pond can be distinguished from other classes based on the NDWI (Figure 5a). Like those of a typical water body, such condition samples usually have NDWI values greater than zero, while those from other classes are generally less than zero. Then, different indices are used to further analyze other conditions. Note that the suspended sediment condition has a low reflection in the NIR band compared to other classes, despite the sediments within the water obstructing some light. The NIR feature values of such condition samples are mostly around 0.1 (Figure 5b). The condition samples of water bloom have higher NDVI values than other classes, except for vegetation (Figure 5c). Therefore, the GLCM entropy is added to differentiate water bloom condition from vegetation. Water bloom condition samples have lower entropy values than vegetation due to their smoother texture (Figure 5d). When the pond water is drained, the mud at the bottom is exposed. As the mud has been soaked in water for a long time, its spectral feature differs from bare soil. The feature values of brightness from a semidry condition sample are generally between 0.08 and 0.12 (Figure 5e).



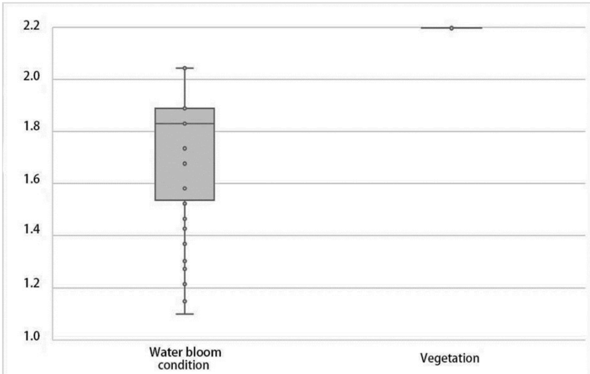
(**a**) NDWI



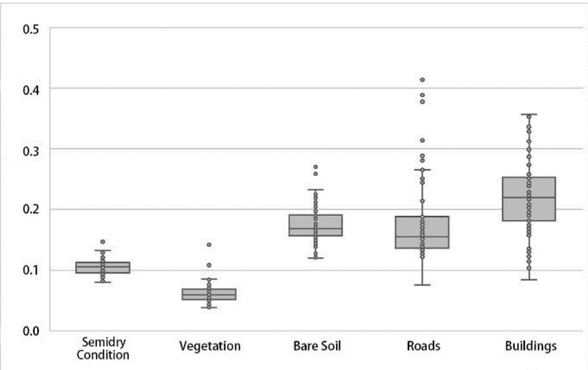
(**b**) NIR



(**c**) NIR



(**d**) GLCM entropy



(**e**) Brightness

Figure 5. The feature values of samples from various classes.

We set the classification rules and their thresholds for method D based on the above feature analysis. The extraction result of method D shows that the multiple pond conditions are identified. As shown in Figure 6a, the pond is in suspended sediment condition and is fully extracted (Figure 6d). The pond in Figure 6b is in water bloom condition, and it is identified in two parts: the main part is a bloom shown in green, and the other part is pure shown in blue (Figure 6e). Four ponds in Figure 6c are in semidry condition; many of them are extracted in red (Figure 6f). These results suggest that method D can extract most of the dike-ponds in multiple pond conditions with different spectral features.

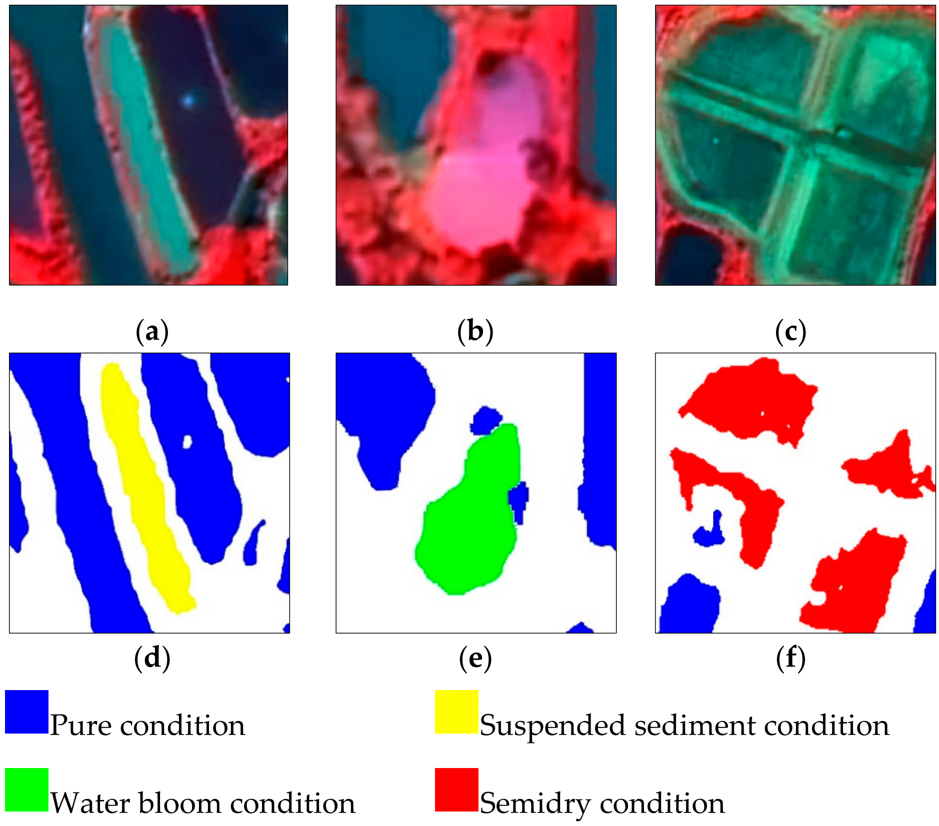
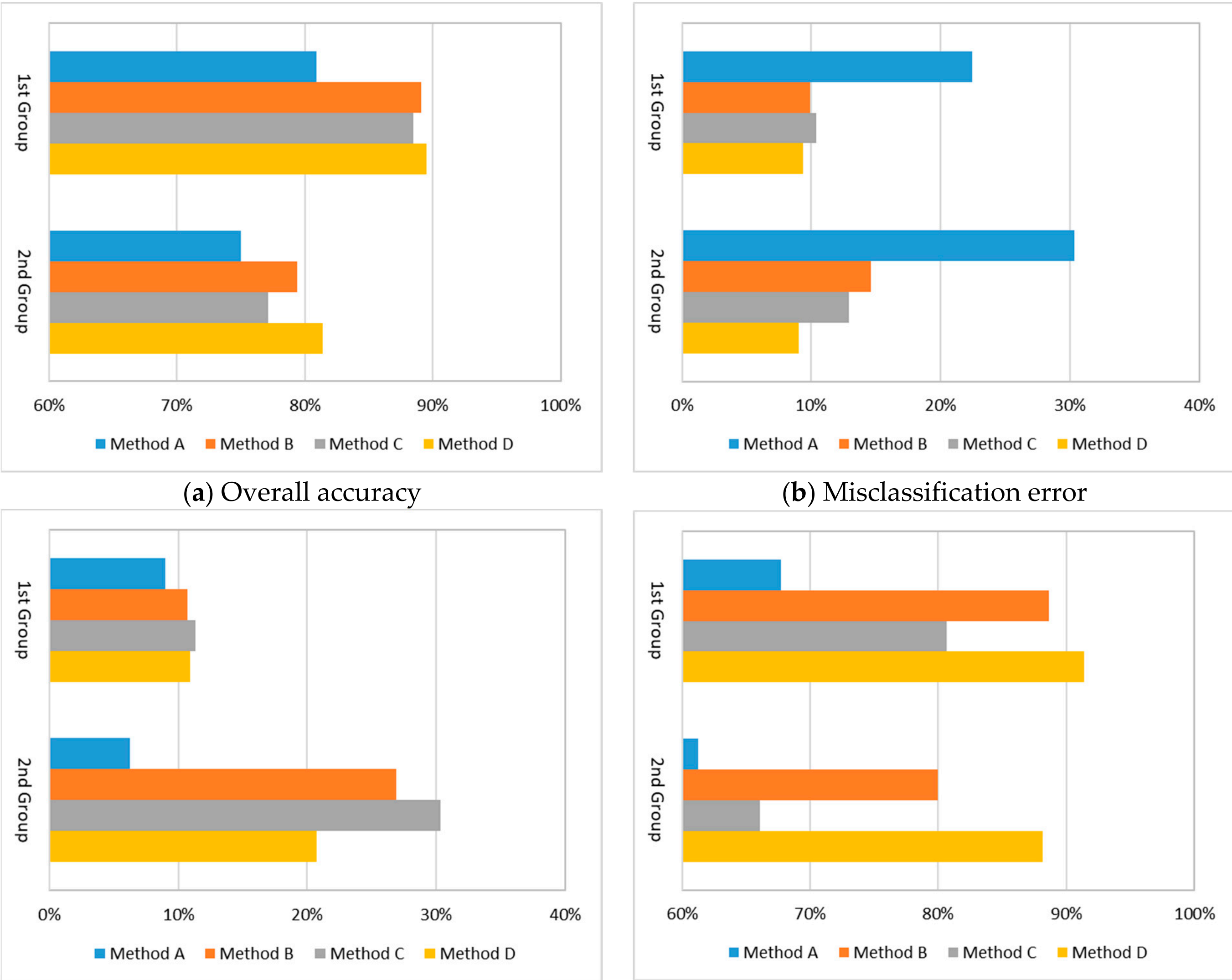


Figure 6. Extraction results of different pond conditions from method D: **a**–**c** are typical images from Gaofen-2 to represent multiple pond conditions, and **d**–**f** are the corresponding classification results.

3.2. Impact Analysis

The impact of multiple pond conditions is explored by comparing the extraction performance of the four methods in the two group regions. Regions #1 and #2 are the first group, and regions #3 and #4 are the second group with more non-pure conditions pond (suspended sediment, water-bloom, semidry). Only 4.59% of the ponds in the first group are non-pure conditions, and up to 15.14% of the ponds in the second group are non-pure conditions. The classification rules of method A, B, and C are not based on multiple pond conditions, whereas method D is.

We analyze the impact on various accuracy measures as the proportion of multiple pond conditions in the test regions increases. The trends of the overall accuracy from the methods are similar in that their measure values are nearly 90% in the first group but drop to around 80% in the second group (Figure 7a). This means overall accuracy decreases as the proportion of multiple pond conditions in the regions increases. In the first group with few pond conditions, the overall accuracy of the methods differs by no more than 1% except for method A. While in the second group, the overall accuracy gap between the methods widens to an average of 4.22%. Method A has the lowest overall accuracy among the four methods in all four regions. The overall accuracy values using methods B and C in the second group are both less than 80% and decrease by an average of 11.89% compared to the first group. Comparing to the other three methods, method D has the highest overall accuracy and maintains an overall accuracy above 80% in the second group. This indicates that the proportion of multiple pond conditions has a negative impact on the overall accuracy measure for all four methods. In addition, the method based on multiple pond conditions is less affected than the method based on a single pond condition.



(**a**) Overall accuracy (**b**) Misclassification error

(**c**) Omission error (**d**) Correct quantity rate

Figure 7. Comparison of accuracy measures of the four methods in two group regions.

Next, we compare the changes in misclassification error and omission error of the four methods. Lower error values indicate better extraction performance. Misclassification error of the methods, except method D, increased from the first group to the second group, with method A increasing by 15.01%, method B increasing by 18.97%, and method C increasing by 10.86% (Figure 7b). The increasing misclassification error means that there are more extracted results which are not true dike-ponds. For example, there are 77.55% in the first group and only 69.62% in the second group of method A results are true dike-ponds. Methods B, C, and D have similar misclassification errors in the first group. However, in the second group, the errors of methods B and C rise to over 13%, while that of method D has hardly changed and remains below 10%. On average, 90.78% of method D results are true dike-ponds. These findings indicate that the increasing proportion of multiple pond conditions increases the misclassification error of the method based on a single pond condition but has little effect on that of the method based on multiple pond conditions.

The omission error of the methods also rose from the first group to the second group (Figure 7c). The exception is method A, which has a low omission error. The other three methods have similar omission errors in the first group, with an average error of 11.02%, and have a higher error in the second group, with an average error of 25.99%. There is an average error gap of 0.31% between methods B/C and method D in the first group, and the gap widened to 7.87% in the second group. That means methods B/C misses more dike-ponds than D when the proportion of multiple pond conditions increases. With multiple pond conditions, it is difficult for most methods to achieve both low errors of misclassification and omission. The misclassification error of B is higher than that of C, and the omission error of B is lower than that of C. There are two spectral rules (NDVI and NIR) in method B, which help it identify more dike-ponds than C. However, method B did not include other rules, such as spatial rules, making its result show more false dike-ponds than C. Method D produces the lowest misclassification error and the second-lowest omission error, as the methods identify multiple pond conditions based on classification rules.

The last measure is the correct quantity rate, which is used to assess the accuracy of dike-pond counting. A similar trend appears in such rate of the four methods; that is, a lower rate in the second group than in the first group (Figure 7d). The decrease is the smallest (3.24%) when using method D, and the other three methods have an average decrease of 9.89%. The different declines indicates that the multiple pond conditions have less impact on the method based on multiple pond conditions. The correct quantity rate is mainly reflected by missed and inaccurately connected ponds, which can be further confirmed by the extraction results. In the region #1 (first row in Figure 8), some missed and connected dike-ponds appear in the result of method A (Figure 8b), and there is not much visual difference in the results of the other three methods (Figure 8c–e). The results of methods A (Figure 8g) and C (Figure 8i) show more missed dike-ponds on the left side of region #2 (second row in Figure 8). In regions #3 and #4 (third and fourth row in Figure 8), method A missed more dike-ponds and connected many separate dike-ponds (Figure 8l,q). When these adjacent ponds are connected, the extracted number is less than the ground truth number. Inaccurate quantity causes a series of dike-pond applications to be unreliable; for example, underestimated number, overestimated average yields, and chaos pattern measurement. Method B missed more dike-ponds and generated fragments at the bottom of region #4 (Figure 8r). Method C extracts fewer dike-ponds than the other three methods in regions (Figure 8n,s). Method D presents fewer missing dike-ponds than the other three methods and keeps most of the adjacent ponds separate (Figure 8o,t), thus avoiding an inaccurate dike-pond quantity reduction. This suggests that method D achieves the highest correct quantity rate at around 90%.

All four accuracy measures prove that the performance of dike-pond extraction deteriorates as the proportion of multiple pond conditions increases. From the first group to the second group, the average degradation of overall accuracy is 8.80%, misclassification error is 3.69%, omission error is 10.53%, and correct quantity rate is 8.23%. An exception is that the omission error of method A is smaller in the second group than the first group. This is primarily because method A sets the rules with a low NDWI threshold to identify more water bodies. However, the cost of this setting is that it has the lowest overall accuracy, highest misclassification error, and lowest correct quantity rate in both the first and second groups (Figure 7).

The classification rules set for multiple pond conditions can mitigate the negative impact of multiple pond conditions on extraction performance. Faced by the regions with more pond conditions, method D has an average of 4.22% higher overall accuracy, 10.25% lower misclassification error, and 19.03% higher correct quantity rate than the other three methods without considering multiple pond conditions. The smaller decrease in performance indicates that considering multiple pond conditions in the extraction method is beneficial for weakening the adverse effects of the increased proportion of pond conditions.

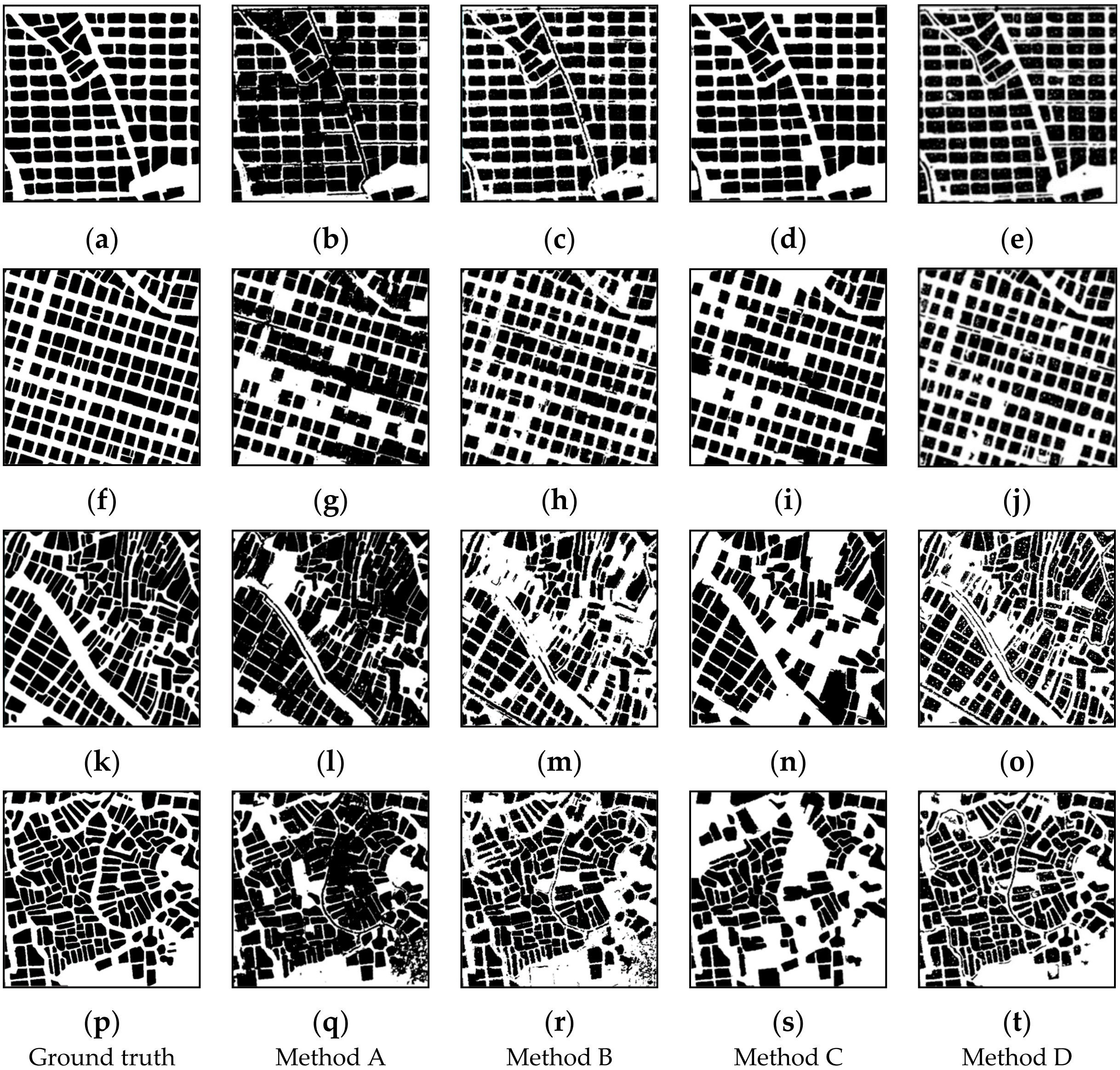


Figure 8. Extraction results of the four tested methods. Each column shows the ground truth or the results of four methods, and each row shows four test regions: (**a**–**e**) are region #1 results, (**f**–**j**) are region #2 results, (**k**–**o**) are region #3 results, and (**p**–**t**) are region #4 results.

4. Discussion

The results of the aforementioned accuracy measures show that all the methods performed worse in the second group of test regions than the first. There may be other causes besides multiple pond conditions, since in reality it is difficult to find two regions that only differ in pond conditions. Nonetheless, the performance degradation is more due to multiple pond conditions, as suggested by the performance gap between methods within the same group. In the first group with less multiple pond conditions, the performance of method D, which sets classification rules for multiple pond conditions, is indistinguishable from the other methods; while in the second group with more multiple pond conditions, assuming the degradation is due to other factors, method D would not outperform the other methods either, but it overthrows the assumption. Furthermore, the distinctive features of different pond conditions are not only confirmed in our feature analysis, but also documented in studies of specific water bodies, such as water bloom [40–42], suspended sediment [43–45], or semidry lake [46,47]. Therefore, it is reasonable to believe that multiple pond conditions are the main cause of performance degradation.

Another concern is the methods used in this paper. We did not demonstrate a novel extraction method, because it is not our goal to develop a new method or choose the best method of dike-pond extraction. The methods are used to explore the impact of multiple pond conditions on the extraction performance. For this purpose, they are primarily derived from existing methods of dike-pond extraction. NDWI is the most popular rule for pond extraction [3,34,48], and for this, methods A, C, and D all contain a similar NDWI rule. NIR rule also appears in existing research, but their functions in the dike-pond extraction are not the same [49,50]. In this paper, method A uses NIR to exclude lakes from dike-ponds. Method B uses it to extract dike-pond regardless of conditions, and method D applies this rule to identify dike-ponds in suspended sediment condition. The methods used in this paper all are rule based, so they can set rules for specific pond conditions, better showings the impact of multiple pond conditions. In contrast, the visual interpretation method is mainly affected by the interpreter [22], and the supervised classification is influenced by the classifier [51,52]. It can be seen that all the four methods have similar indices and processes; hence, they are comparable. Among considerable existing methods, the methods we used are representative. Method A represents those methods that attempt to extract more ponds (low omission error), but few of their results are true dike-ponds (high misclassification error). Methods B and C represent those methods that tried to reduce the false extraction but identified few ponds. The extraction results demonstrated that the methods based on a single pond condition perform poorly in the regions with multiple pond conditions, since they hardly strike a balance between extracting as many ponds as possible and ensuring that the extracted ponds are correct as much as possible.

Our research contributes a reference for those pond extraction studies that required high classification accuracy. Using high-resolution image data (e.g., Sentinel [30,53] and Worldview [33] satellites) or powerful classification methods (e.g., support vector machines [54] and deep learning [27,55]) are two major ways to capture high accuracy. To further improve the accuracy based on the data and method, the characteristics of the extracted objects can be incorporated into the method design and processing flow of the extraction. On the basis of this study, it can be expected that considering multiple pond conditions in pond extraction can achieve better accuracy than the same method and the same data without considering pond condition. Higher accuracy means that dike-pond mapping has more complete size, more accurate quantity, and more precise shape, which are beneficial for dike-pond applications [13,16,23,56]. For example, fishery production estimate is based on size, pond productivity comparison is based on quantity, pond pattern analysis is based on shape, and dike-pond landscape dynamics tracking is based on spatiotemporal mapping.

Other potential dike-pond applications can also be inspired by our research, such as the assessment of pond degradation. As integrated agricultural systems, dike-ponds play an important role in ecological sustainability, such as purifying water quality, stabilizing water bodies, and maintaining aquatic biodiversity. Within our study area, pollutants from widely used synthetic fertilizers and medicine are damaging the ecosystem service of dike-ponds [57,58]. Some publications have focused on examining dike-pond system degradation and restoration [9,59]. In contrast with these studies, our research identifies dike-ponds in suspended sediment, water bloom, and semidry conditions from remote sensing images, indicating that our method has the potential application to monitor the health of dike-ponds. We can construct an evaluation system inspired by our research idea of formulating classification rules for multiple pond conditions. The evaluation indices are selected according to the feature of different pond health states, and then based on the statistical value of the sample measurement data to make the index screening process more flexible and targeted. Water managers use this evaluation system to monitor the health state of ponds: where are the unhealthy ponds and how many are there? Improvement measures will be carried out when unhealthy ponds are found, so as not to disrupt fishery production. For example, a water bloom indicates an overgrowth of algae which can lead to the death of organisms in the pond. Using time-dependent evaluating before and after implementation, water managers can obtain the change in pond health and assess the effective of the measures on water ecological restoration. These quantitative dike-pond resource management and developmental environmental restoration methods can be considered in future research.

5. Conclusions

In summary, after comparing the performance of the four methods in the two groups' test regions, we concluded that multiple pond conditions are essential for the performance of dike-pond extraction. As the proportion of multiple pond conditions in the region increases, various measure values deteriorate—the average of overall accuracy, misclassification error, omission error, and correct quantity rate dropped by 8.80%, 3.69%, 10.53%, and 8.23%, respectively. In addition, the extraction performance between most of the methods does not differ much in the regions with few multiple pond conditions. However, in the regions with more multiple pond conditions, the method of classification rules setting for multiple pond conditions can weaken the negative impact of multiple pond conditions. It reduced performance degradation by 4.22% in overall accuracy, 10.25% in misclassification error, and 19.03% in correct quantity rate compared to the other three methods not based on multiple pond conditions. These findings provide insight into the impact of multiple pond conditions on extraction performance. We recommend considering non-pure pond conditions (e.g., suspended sediment, water bloom, semidry) in the extraction method, which is beneficial for dike-pond applications that require complete extraction of ponds, not just ponds in pure condition.

Author Contributions: J.Z. and Y.Z. conceived the study conception, design, and methodology. J.Z., Q.Z., W.Z., F.X. and S.L. conducted the fieldwork and data analysis. J.Z., Q.Z. and Y.Z. interpreted results and co-wrote the manuscript. Y.H. commented on previous versions of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China (Grant 42001213), Natural Science Foundation of Guangdong Province, China (Grant. 2018A030313201), and China Scholarship Council.

Data Availability Statement: The data that support our results are available from the corresponding author upon request.

Acknowledgments: We thank the students Haitao Jiang, Junpeng Li, and Shaofang Huang from South China Agricultural University, and Y. Lain for their help. We especially thank the reviewers for their insightful comments.

Conflicts of Interest: The authors have no relevant financial or non-financial interests to disclose.

References

1. Edwards, P. Aquaculture environment interactions: Past, present and likely future trends. *Aquaculture* **2015**, *447*, 2–14. [CrossRef]
2. Nagamani, K.; Suresh, Y. Evaluation of coastal aquaculture ponds using remote sensing and GIS. *Indian J. Geo-Mar. Sci.* **2019**, *48*, 1205–1209.
3. Ren, C.; Wang, Z.; Zhang, Y.; Zhang, B.; Chen, L.; Xi, Y.; Xiao, X.; Doughty, R.B.; Liu, M.; Jia, M.; et al. Rapid expansion of coastal aquaculture ponds in China from Landsat observations during 1984–2016. *Int. J. Appl. Earth Obs.* **2019**, *82*, 101902. [CrossRef]
4. Chan, G.L. Aquaculture, Ecological Engineering: Lessons from China. *Ambio* **1993**, *22*, 491–494.
5. Weng, Q. A historical perspective of river basin management in the Pearl River Delta of China. *J. Environ. Manag.* **2007**, *85*, 1048–1062. [CrossRef] [PubMed]
6. Li, W.H.; Min, Q.W. Integrated farming systems an important approach toward sustainable agriculture in China. *Ambio* **1999**, *28*, 655–662.
7. Guo, S. The research into the world heritage value and tourism development of Dike-Pond agriculture in the pearl river delta. In *Tourism and Hospitality Development Between China and EU*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 111–127.
8. Gongfu, Z. The types, structure and results of the dike-pond system in South China. *GeoJournal* **1990**, *21*, 83–89. [CrossRef]
9. Lo, C.P. Environmental impact on the development of agricultural technology in China: The case of the dike-pond ("jitang") system of integrated agriculture-aquaculture in the Zhujiang Delta of China. *Agric. Ecosyst. Environ.* **1996**, *60*, 183–195. [CrossRef]
10. Korn, M. The dike-pond concept: Sustainable agriculture and nutrient recycling in China. *Ambio* **1996**, *25*, 6–13.

11. Peng, J.; Wang, Y.L.; Jing, J.; Yue, J.; Li, W.F. Ecological development of coastal areas in China. *Coast. Manag.* **2005**, *33*, 167–179. [CrossRef]
12. Astudillo, M.F.; Thalwitz, G.; Vollrath, F. Modern analysis of an ancient integrated farming arrangement: Life cycle assessment of a mulberry dyke and pond system. *Int. J. Life Cycle Ass.* **2015**, *20*, 1387–1398. [CrossRef]
13. Li, F.; Liu, K.; Tang, H.; Liu, L.; Liu, H. Analyzing trends of dike-ponds between 1978 and 2016 using multi-source remote sensing images in shunde district of south China. *Sustainability* **2018**, *10*, 3504. [CrossRef]
14. Tian, M. Seeing from above: Observation of contemporary dike-pond landscape. *Landsc. Archit. Front.* **2019**, *7*, 130–138. [CrossRef]
15. Klemas, V. Fisheries applications of remote sensing: An overview. *Fish. Res.* **2013**, *148*, 124–136. [CrossRef]
16. Ottinger, M.; Clauss, K.; Kuenzer, C. Opportunities and challenges for the estimation of aquaculture production based on earth observation data. *Remote Sens.* **2018**, *10*, 1076. [CrossRef]
17. Kourti, N.; Shepherd, I.; Greidanus, H.; Alvarez, M.; Aresu, E.; Bauna, T.; Chesworth, J.; Lemoine, G.; Schwartz, G. Integrating remote sensing in fisheries control. *Fish. Manag. Ecol.* **2005**, *12*, 295–307. [CrossRef]
18. Putri, A.; Zainuddin, M. Application of remotely sensed satellite data to identify Skipjack Tuna distributions and abundance in the coastal waters of Bone Gulf. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *241*, 12012. [CrossRef]
19. Saitoh, S.; Mugo, R.; Radiarta, I.N.; Asaga, S.; Takahashi, F.; Hirawake, T.; Ishikawa, Y.; Awaji, T.; In, T.; Shima, S. Some operational uses of satellite remote sensing and marine GIS for sustainable fisheries and aquaculture. *Ices J. Mar. Sci.* **2011**, *68*, 687–695. [CrossRef]
20. Fu, T.; Zhang, L.; Yuan, X.; Chen, B.; Yan, M. Spatio-temporal patterns and sustainable development of coastal aquaculture in Hainan Island, China: 30 Years of evidence from remote sensing. *Ocean Coast. Manag.* **2021**, *214*, 105897. [CrossRef]
21. Liu, J.; Chen, J.; Wang, X. Spatial-temporal Change of Sanshui district's Dike-pond from 1979–2009. *Phys. Procedia* **2012**, *25*, 452–458. [CrossRef]
22. Li, Y.; Liu, K.; Liu, Y.; Zhu, Y. The dynamic of dike-pond system in the pearl river delta during 1964–2012. In *Global Changes and Natural Disaster Management: Geo-Information Technologies*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 47–59.
23. Liu, G.; Li, J. Tracking dike-pond landscape dynamics in a core region of the Guangdong-Hong Kong-Macao Greater Bay Area based on topographic maps and remote sensing data during 1949–2020. *Aquaculture* **2022**, *549*, 737741. [CrossRef]
24. Yee, A.W.C. New developments in integrated dike-pond agriculture-aquaculture in the Zhujiang Delta, China: Ecological implications. *Ambio* **1999**, *28*, 529–533.
25. Virdis, S.G.P. An object-based image analysis approach for aquaculture ponds precise mapping and monitoring: A case study of Tam Giang-Cau Hai Lagoon, Vietnam. *Environ. Monit. Assess.* **2014**, *186*, 117–133. [CrossRef] [PubMed]
26. Duan, Y.; Tian, B.; Li, X.; Liu, D.; Sengupta, D.; Wang, Y.; Peng, Y. Tracking changes in aquaculture ponds on the China coast using 30 years of Landsat images. *Int. J. Appl. Earth Obs.* **2021**, *102*, 102383. [CrossRef]
27. Ma, Y.; Zhou, Z.; She, X.; Zhou, L.; Ren, T.; Liu, S.; Lu, J. Identifying dike-pond system using an improved cascade R-CNN model and High-Resolution satellite images. *Remote Sens.* **2022**, *14*, 717. [CrossRef]
28. Zhang, T.; Li, Q.; Yang, X.; Zhou, C.; Su, F. Automatic mapping aquaculture in coastal zone from TM imagery with OBIA approach. In Proceedings of the 2010 18th International Conference on Geoinformatics, Beijing, China, 18–20 June 2010.
29. Loberternos, R.A.; Porpetcho, W.P.; Graciosa, J.C.A.; Violanda, R.R.; Diola, A.G.; Dy, D.T.; Otadoy, R.E.S. An object-based workflow developed to extract aquaculture ponds from airborne lidar data: A test case in central visayas, philippines. In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*; ISPRS Congress: Prague, Czech Republic, 2016; Volume 41, pp. 1147–1152.
30. Ottinger, M.; Clauss, K.; Kuenzer, C. Large-Scale assessment of coastal aquaculture ponds with sentinel-1 time series data. *Remote Sens.* **2017**, *9*, 440. [CrossRef]
31. Chen, Y. *Estimation of Ponds Area Based on Object-Oriented Classification Method with Remote Sensing Data: A Case of Taishan*; Nanjing University: Nanjing, China, 2011.
32. Zhao, J.; Lin, M.; Gong, J.; Li, T. Analysis on Landscape Pattern Based on Extraction of Dike-Pond Ecosystem Using Object-Oriented Classification Method in Shunde District. *Ecol. Sci.* **2018**, *37*, 191–197.
33. Li, F.; Liu, K.; Liu, Y.; Tang, H.; Liu, L.; Peng, L. Remote sensing classification for dike-pond system based on Worldview-2 data. *Wetl. Sci.* **2018**, *16*, 587–596.
34. Al Sayah, M.J.; Nedjai, R.; Abdallah, C.; Khouri, M. On the use of remote sensing to map the proliferation of aquaculture ponds and to investigate their effect on local climate, perspectives from the Claise watershed, France. *Environ. Monit. Assess.* **2020**, *192*, 301. [CrossRef]
35. Hay, A.M. The derivation of global estimates from a confusion matrix. *Int. J. Remote Sens.* **1988**, *9*, 1395–1398. [CrossRef]
36. Mcfeeters, S.K. The use of the normalized difference water index (NDWI) in the delineation of open water features. *Int. J. Remote Sens.* **1996**, *17*, 1425–1432. [CrossRef]
37. Gao, B. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sens. Environ.* **1996**, *58*, 257–266. [CrossRef]
38. Rouse, J.W. Monitoring Vegetation Systems in the Great Plains with Erts. In Proceedings of the Third ERTS Symposium, Washington, DC, USA, 10–14 December 1973; NASA: Washington, DC, USA, 1973; pp. 309–317.
39. Haralick, R.M.; Shanmugam, K.; Dinstein, I. Textural features for image classification. *IEEE Trans. Syst. Man Cybern.* **1973**, *SMC-3*, 610–621. [CrossRef]

40. Fan, Y.; Chen, Y.; Chen, X.; Zhang, H.; Liu, C.; Duan, Q. Estimating the aquatic-plant area on a pond surface using a hue-saturation-component combination and an improved Otsu method. *Comput. Electron. Agric.* **2021**, *188*, 106372. [CrossRef]
41. Mishra, S.; Stumpf, R.P.; Meredith, A. Evaluation of RapidEye data for mapping algal blooms in inland waters. *Int. J. Remote Sens.* **2019**, *40*, 2811–2829. [CrossRef]
42. Edna, G.; Fernandez-Figueroa, A.E.W.S. Commercially available unoccupied aerial systems for monitoring harmful algal blooms: A comparative study. *Limnol. Oceanogr. Meth.* **2022**, *20*, 146–158.
43. Volpe, V.; Silvestri, S.; Marani, M. Remote sensing retrieval of suspended sediment concentration in shallow waters. *Remote Sens. Environ.* **2011**, *115*, 44–54. [CrossRef]
44. Marinho, R.R.; Harmel, T.; Martinez, J.; Filizola Junior, N.P. Spatiotemporal dynamics of suspended sediments in the negro river, amazon basin, from in situ and sentinel-2 remote sensing data. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 86. [CrossRef]
45. Cheng, C.; Wei, Y.; Xu, J.; Yuan, Z. Remote sensing estimation of Chlorophyll a and suspended sediment concentration in turbid water based on spectral separation. *Optik* **2013**, *124*, 6815–6819. [CrossRef]
46. Gao, S.; Li, Z.; Chen, M.; Allen, D.; Neeson, T.; Hong, Y. Monitoring drought through the lens of landsat: Drying of rivers during the california droughts. *Remote Sens.* **2021**, *13*, 3423. [CrossRef]
47. Wang, S.; Zhang, L.; Zhang, H.; Han, X.; Zhang, L. Spatial-temporal wetland landcover changes of Poyang lake derived from landsat and HJ-1A/B data in the dry season from 1973–2019. *Remote Sens.* **2020**, *12*, 1595. [CrossRef]
48. Watson, C.S.; King, O.; Miles, E.S.; Quincey, D.J. Optimising NDWI supraglacial pond classification on Himalayan debris-covered glaciers. *Remote Sens. Environ.* **2018**, *217*, 414–425. [CrossRef]
49. Mondejar, J.P.; Tongco, A.F. Near infrared band of Landsat 8 as water index: A case study around Cordova and Lapu-Lapu City, Cebu, Philippines. *Sustain. Environ. Res.* **2019**, *29*, 16. [CrossRef]
50. Kim, G.; Baek, I.; Stocker, M.D.; Smith, J.E.; Van Tassell, A.L.; Qin, J.; Chan, D.E.; Pachepsky, Y.; Kim, M.S. Hyperspectral imaging from a multipurpose floating platform to estimate chlorophyll-a concentrations in irrigation pond water. *Remote Sens.* **2020**, *12*, 2070. [CrossRef]
51. Briem, G.J.; Benediktsson, J.A.; Sveinsson, J.R. Multiple classifiers applied to multisource remote sensing data. *IEEE T. Geosci. Remote Sens.* **2002**, *40*, 2291–2299. [CrossRef]
52. Talukdar, S.; Singha, P.; Mahato, S.; Shahfahad; Pal, S.; Liou, Y.; Rahman, A. Land-Use Land-Cover classification by machine learning classifiers for satellite observations—A review. *Remote Sens.* **2020**, *12*, 1135. [CrossRef]
53. Quantifying suspended sediment dynamics in mega deltas using remote sensing data: A case study of the Mekong floodplains. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *68*, 105–115.
54. Zeng, Z.; Wang, D.; Tan, W.; Huang, J. Extracting aquaculture ponds from natural water surfaces around inland lakes on medium resolution multispectral images. *Int. J. Appl. Earth Obs.* **2019**, *80*, 13–25. [CrossRef]
55. Zeng, Z.; Wang, D.; Tan, W.; Yu, G.; You, J.; Lv, B.; Wu, Z. RCSANet: A full convolutional network for extracting inland aquaculture ponds from High-Spatial-Resolution images. *Remote Sens.* **2021**, *13*, 92. [CrossRef]
56. Jinhao, Z.; Xiaojun, H.; Ningchuan, X.; Zeming, L.; Manqi, L. Comparison and application of spatial pattern measurement methods for water surface of dike-pond. *Trans. Chin. Soc. Agric. Eng.* **2021**, *37*, 251–257.
57. Zhang, W.; Cheng, Z.; Qiu, J.; Park, E.; Ran, L.; Xie, X.; Yang, X. Spatiotemporal Changes in Mulberry-Dyke-Fish Ponds in the Guangdong-Hong Kong-Macao Greater Bay Area over the Past 40 Years. *Water* **2021**, *13*, 2953. [CrossRef]
58. Mhw, A.; Kcc, A.; Ay, B.; Ckcw, A. The Dyke-pond systems in south china: Past, present and future—ScienceDirect. In *Wetlands Ecosystems in Asia*; Springer: Berlin/Heidelberg, Germany, 2004; pp. 47–66.
59. Nie, C.; Luo, S.; Zhang, J.; Li, H.; Zhao, Y. The dike-pond system in the Pearl River Delta: Degradation following recent land use alterations and measures for their ecological restoration. *Acta Ecol. Sin.* **2003**, *23*, 1851–1860.