Sains Malaysiana 51(2)(2022): 369-378
http://doi.org/10.17576/jsm-2022-5102-04

Comparison of Three Water Indices for Tropical Aquaculture Ponds Extraction using Google Earth Engine

(Perbandingan Tiga Indeks Air untuk Pengekstrakan Kolam Akuakultur Tropika menggunakan *Google Earth Engine*)

YI LIN TEW, MOU LEONG TAN, NARIMAH SAMAT*, NGAI WENG CHAN, MOHD AMIRUL MAHAMUD, MUHAMMAD AZIZAN SABJAN, LAI KUAN LEE, KOK FONG SEE & SEOW TA WEE

ABSTRACT

Information on the spatial distribution of aquaculture ponds, especially the inland brackish aquaculture, is crucial for effective and sustainable aquaculture management. Google Earth Engine (GEE) has been utilized to quickly map aquaculture ponds in different parts of the world, but the application is still limited in tropical regions. Selection of an optimal water index is essential to accurately map the aquaculture ponds from the Landsat 8 satellite images that are available in GEE. This study aims to evaluate the capability of three different water indices, namely Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI) and Automated Water Extraction Index (AWEI), in mapping of the aquaculture ponds in Sungai Udang, Pulau Pinang, Malaysia. The results show that MNDWI is the best index for aquaculture ponds extraction in Sungai Udang, with an accuracy of 81.87% and Kappa coefficient of 0.61. Meanwhile, the accuracy of NDWI and AWEI as compared to the digitized aquaculture ponds are 58.21 and 61.60%, and Kappa coefficient of 0.33 and 0.36, respectively. Then, MNDWI was applied to calculate the spatial changes of aquaculture ponds from 2014 to 2020. The result indicates that the area of aquaculture ponds has expanded by 26.16% since the past seven years.

Keywords: Aquaculture; Google Earth Engine; Landsat; Malaysia; tropical

ABSTRAK

Maklumat ruang kolam akuakultur terutamanya kolam akuakultur air payau pedalaman adalah penting dalam keberkesanan pengurusan akuakultur yang lestari. Google Earth Engine *(GEE) telahpun dimanfaatkan dalam pemetaan kolam akuakultur di beberapa negara, namun aplikasinya di kawasan tropika masih kurang. Pemilihan indeks air yang sesuai boleh memetakan kolam akuakultur dengan tepat daripada imej Landsat 8 dengan menggunakan GEE. Kajian ini bertujuan untuk menilai kemampuan tiga jenis indeks air yang bernama* Normalized Difference Water Index *(NDWI),* Modified Normalized Difference Water Index *(MNDWI) dan* Automated Water Extraction Index *(AWEI) dalam pemetaan kolam akuakultur di Sungai Udang, Pulau Pinang. Hasil daripada kajian ini, MNDWI menunjukkan ketepatan yang paling tinggi dalam memetakan kolam akuakultur di Sungai Udang, dengan ketepatan sebanyak 81.87% dan nilai pekali Kappa 0.61. Manakala bagi NDWI dan AWEI pula, ketepatan kedua-dua indeks air ini adalah 58.21 dan 61.60%, serta nilai pekali Kappa 0.33 dan 0.36 sahaja. Dengan ini, MNDWI telah diguna untuk memperoleh perubahan ruang kawasan kolam-kolam akuakultur di Sungai Udang dari tahun 2014 sehingga 2020. Hasilnya menunjukkan kawasan kolam-kolam ini telah berkembang sebanyak 26.16% dalam masa tujuh tahun.*

Kata kunci: Akuakultur; Google Earth Engine*; Landsat; Malaysia; tropika*

INTRODUCTION

The Food and Agricultural Organization (FAO 2020) reported that the fish consumption has increased significantly from 5.2 kg/capita in 1961 to 19.4 kg/capita in 2017 due to the expansion of fish production and imports. In fact, Malaysia is one of the highest consumers of fish in the world, with 59 kg/capita in 2016 (Khor et al. 2020). Due to the decline in marine-capture fish production, aquaculture has become a crucial source for supplying protein to human beings in the future. The rapid expansion of aquaculture ponds has led to significant harm to the surrounding environment and ecosystems. However, information on the aquaculture pond' distribution and pattern are still incomplete in many countries, including Malaysia. Therefore, remote sensing and Geographical Information System (GIS) play a vital role in providing the basic geospatial information of aquaculture ponds for effective and sustainable aquaculture management.

Google Earth Engine (GEE) is a powerful cloud-based platform for processing very large amounts of over 40 years' satellite images, without the need of high-performance computer systems and huge data storage devices (Gorelick et al. 2017). In particular, GEE users manage to search millions of individual images and select the most appropriate images based on user-defined spatial, spectral and temporal criteria. GEE has become popular since 2013 (Tamiminia et al. 2020), focusing in the applications of land use change detection (Ghorbanian et al. 2020; Zurqani et al. 2018), forest mapping (Koskinen et al. 2019), disaster reduction (DeVries et al. 2020), crop monitoring (You & Dong 2020) and water management (Worden & de Beurs 2020).

Visual interpretation is commonly used to extract the aquaculture ponds from satellite imagery. Several researchers have applied an automated extracted approach to utilize the GEE in aquaculture pond mapping. Xia et al. (2020) automatically extracted the aquaculture ponds from 2016 to 2019 in Shanghai, China, using GEE. A similar study has been conducted by Duan et al. (2020) in Jiangsu province for a longer time period of 1988 to 2018. With the help of GEE, Duan et al. (2019) conducted a national scale GEE-based aquaculture ponds mapping for the east coast China and reported the total aquaculture land area of about 15632.64 km^2. However, the application of GEE in extracting the spatial distribution of aquaculture ponds is still limited in tropical regions.

To improve the detection of aquaculture ponds, the outcomes from different data sources, classification methods or water indices can be firstly compared for selecting the optimal inputs and methods. Water index plays a critical role to detect and delineate surface water by emphasizing the spectral characteristics of water features using band math. For instance, Worden and de Beurs (2020) found the modified Normalized Difference Water Index (MNDWI) performed better than the Automated Water Extraction Index (AWEI) and the Normalized Different Water Index (NDWI) (McFeeters 1996) for extracting surface water in the Caucasus. A further investigation on identifying a suitable water index is needed for extracting tropical aquaculture ponds under the GEE platform.

This study aims to compare three water indices, MNDWI, NDWI, and AWEI, in aquaculture pond mapping using GEE. Then, the optimal water index was used to detect the spatial distribution of aquaculture ponds in Sungai Udang that were located in southwestern part of Pulau Pinang from 2014 to 2020. The findings of this study can be used as a reference for developing better water indexes to extract aquaculture ponds in tropical regions.

Materials and Methods

STUDY AREA

Sungai Udang is located in the south-western part of Penang, Malaysia, between longitudes of 100°23'49.6"E and 100°28'01.8"E and latitudes of 5°07'13.1"N and 5°11'31.5"N, was selected as study site. This area belongs to the tropical monsoon climate which receives high amounts of precipitation and sunlight throughout the year. Lying along the seaside and the river mouth, the topography of the study area is flat, with the majority of the land cover type of agriculture (Tew et al. 2019), making Sungai Udang a geographically and environmentally suitable place for inland aquaculture activities. Sungai Udang is a Chinese fishery village and famous local seafood wholesale market in Penang (Lim 2015). Figure 1 shows the aquaculture ponds are usually in rectangular shape to raise different type of fishes, prawns, cuttlefish and crabs.

DATA COLLECTION

Landsat 8 is the eighth satellite in the Landsat program under the American Earth observation satellite that launched on 11 February 2013. The Landsat 8 images are freely available to the public for studies related to the Earth system. Landsat 8 Operational Land Imager (OLI)/ Thermal Infrared Sensor (TIRS) image collection from 2014 to 2020 in the GEE were used in this study. One of the advantages of using satellite images from GEE is to obtain cloud-masked images from the collections directly with the established GEE algorithms (Aziz et al. 2020). The broad spectral range of Landsat 8 enables top-of-atmosphere radiances for various types of surfaces with OLI to show higher response among different bands (Barsi et al. 2014). The infrared bands in the sensor enabled water pixels' delineation more explicit.

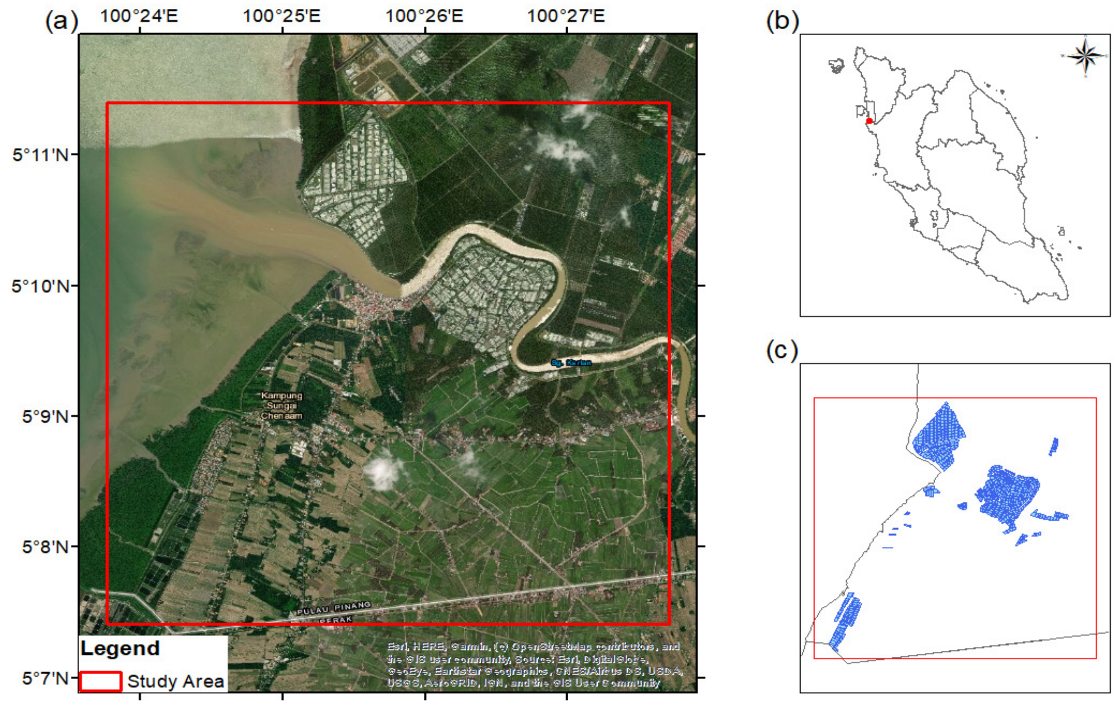

FIGURE 1. Study area map: (a) location of Sg Udang in Penang; (b) location of study area in Peninsular Malaysia; (c) distribution of the aquaculture ponds digitized from the GEE

WATER INDEX

Mapping of the earth surface and open water surface with remote sensing technology is a common practice around the world (Wang et al. 2020b). One of the methods for open surface waterbody mapping is through water indices (Chen et al. 2020a, 2020b; Wang et al. 2020a), because it is easy to implement at low computational errors. The three common water indices used in surface water extraction are the NDWI, MNDWI and AWEI.

Water index is a multispectral band rationing technique that reduces a large proportion of the topographic effect, making the scattered reflectance dependent from light diffusion (Holben & Justice 1981). Gao (1996) proposed NDWI that made use of two narrow channels cantered near 0.86 and 1.24 µm, which is the green and near infrared (NIR) band. Later, Xu (2006) introduced a modified version of NDWI by substituting the NIR with the middle infrared band (MIR) that can be found in band 5 in Landsat TM or band 6 in Landsat OLI. MNDWI returns greater differences between water, pasture and vegetation surfaces.

With the recommendation addressed by Ji et al. (2009) and Xu (2006), the implementation of NDWI threshold should be adjusted to match a reference dataset with finer resolution, for example, involving the Short Wave Infrared (SWIR) band, in order to map the surface water features. As mapping of water pixels adopts reflectance in the infrared bands, water classification may encounter obstacle on shadow from mountains, buildings and roads. Therefore, Feyisa et al. (2014) introduced the AWEI that implied five spectral bands to maximize separability of water and non-watery pixels through band differencing and different coefficients. The equations of the water indices are expressed as below:

$$NDWI = \frac{(\rho_{green} - \rho_{NIR})}{(\rho_{green} + \rho_{NIR})} \quad (1)$$

$$MNDWI = \frac{(\rho_{green} - \rho_{SWIR1})}{(\rho_{green} + \rho_{SWIR1})} \quad (2)$$

$$AWEI_{nsh} = 4 \times (\rho_{green} - \rho_{SWIR1}) - (0.25 \times \rho_{NIR} + 2.75 \times \rho_{SWIR2}) \quad (3)$$

$$AWEI_{sh} = \rho_{blue} + 2.5 \times \rho_{green} - 1.5 \times (\rho_{NIR} + \rho_{SWIR1}) - 0.25 \times \rho_{SWIR2} \quad (4)$$

where in Landsat 8 imagery, ρ_{green} equals to the band 3; ρ_{NIR} equals to band 5; ρ_{SWIR1} equals to band 6 and ρ_{SWIR2} equals to band 7.

According to Feyisa et al. (2014), the two AWEI algorithms can be used separately or together. However, due to the presence of a highly reflective surface in our study area that existed on the zinc rooftop around the aquaculture farms (Yu et al. 2020), therefore, only the $AWEI_{nsh}$ was adopted in this study.

GOOGLE EARTH ENGINE

GEE is a cloud-based platform for large geospatial datasets at minimal computing resource access with JavaScript (Gorelick et al. 2017). In order to achieve openness in geospatial research, the GEE has a big research community for result sharing and problem discussions. Another advantage of using GEE is the ready-to-use Earth Engine public data catalogue that enables users to retrieve the time series satellite imagery collection archive (Amani et al. 2020).

In this study, the cloud-mask Landsat 8 image collection function in GEE was used to produce cloud-free images. The cloud masking was done in the way that the multi-level cloud detection models stored as APIs in GEE filtered the cloud contains and automatically ignored the pixels that were recognized as cloud and replaced by the historical cloud-free dataset (Yin et al. 2020).

The derivation of the band ratios is done within the GEE platform with the Earth Engine APIs (Nguyen et al. 2019) according to the indices that we have identified earlier. Spectral filtering was done by setting the threshold for masking out pixels with values higher than 0, according to the theory of positive values indicating water bodies. The extracted water bodies in 2020 were then exported for accuracy assessment with geographic information system (GIS) software.

A total of 590 aquaculture ponds that have been digitized from Google Earth Pro's high-resolution satellite images were used as references to validate the mapping of aquaculture ponds. The consumer accuracy and Kappa coefficient approaches were used in the accuracy assessment. The consumer accuracy is the percentage of correctly classified pixels to the total number of pixels, meanwhile the Kappa coefficient is an agreement indicator between the classified pixels with the ground truth. The methods workflow of this study is shown as in Figure 2.

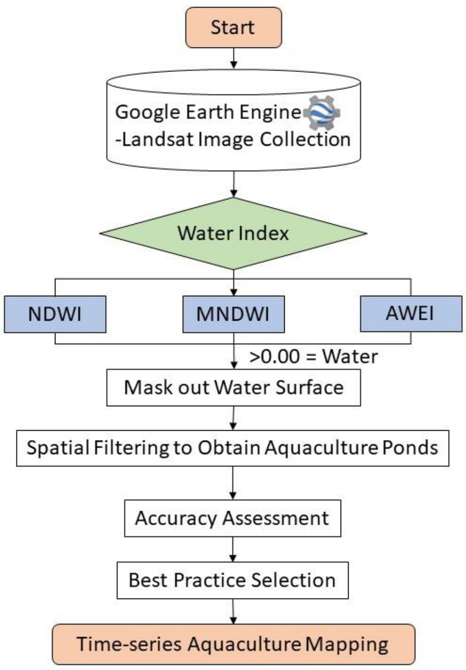

FIGURE 2. Methods flowchart of this study

Results and Discussion

PERFORMANCE OF THE WATER INDICES

The threshold for water pixel extraction is set constant at 0 for NDWI, MNDWI, and AWEI, as recommended by Zhai et al. (2020). Table 1 shows the statistical results of the accuracy assessment for all the three water indices. Whereas, the band rationing resulted in images shown in Figure 3. In general, the performance of MNDWI is the best among the evaluated water indices. The accuracy of MNDWI in mapping the aquaculture ponds is 81.87%, with a Kappa coefficient of 0.61, which means the result shows a substantial agreement. The superior performance of MNDWI in surface water extraction was also reported by Ji et al. (2009). Meanwhile, for the performance of NDWI and AWEI, the accuracy computed was 58.21 and 61.60% and the Kappa coefficient of 0.33 and 0.36, which showed a fair agreement.

TABLE 1. Performance of each water indices in mapping aquaculture pond of year 2020

Year	Parameter	Percentage %	Kappa Coefficient
2020	NDWI	58.21	0.33
2020	MNDWI	81.87	0.61
2020	AWEI	61.60	0.36

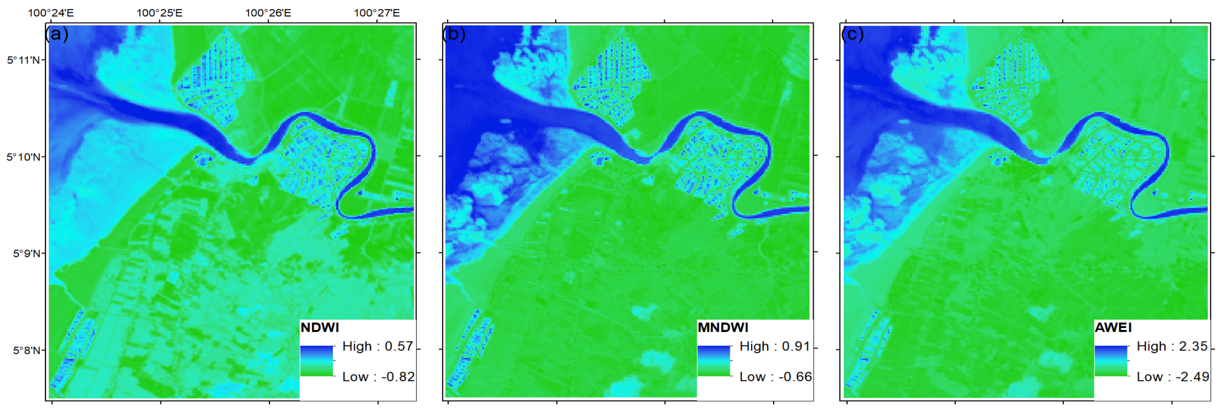

FIGURE 3. Result raster for each water indices: (a) NDWI; (b) MNDWI; (c) AWEI

By looking at the values of the water indices separately, AWEI returned a larger water index range as compared to NDWI and MNDWI. This large gap made the differentiation between water and non-water pixels more significant, therefore creating a clearer edge boundary than NDWI. However, the aquaculture pond characteristics by AWEI were not distinctive compared to those with MNDWI.

However, water-containing pixels may be referred to vegetation covers as well. For example, the NIR band in NDWI was found to extract moisture from vegetation, as oil palm is dominant in the study area. Therefore, the evapotranspiration from oil palm plantations was reflected in the NDWI extracted map. Besides that, NDWI showed negative values for mixed water pixels, which matches with the results obtained by Ji et al. (2009). For instance, the majority of the aquaculture ponds resulted in negative values, as shown in Figure 3(a). By contrast, the characteristics of MNDWI that are considered the Short Wave Infrared 1 (SWIR1) band with a finer spectral wavelength can better capture the aquaculture ponds due to the lesser interference of evapotranspiration from vegetation covers.

According to Feyisa et al. (2014), AWEI demonstrated a good performance in extracting water pixels from shadow at high albedo features due to the broader range of wavelengths in the band rationing. As Sungai Udang is situated near to the river mouth with flat terrain (Figure 4(c)), the albedo variation caused by the shadow effect was not high, thus AWEI might not be the most suitable index to be used to map our aquaculture ponds. In fact, AWEI is more suitable to be applied in urbanized regions with a higher albedo variation.

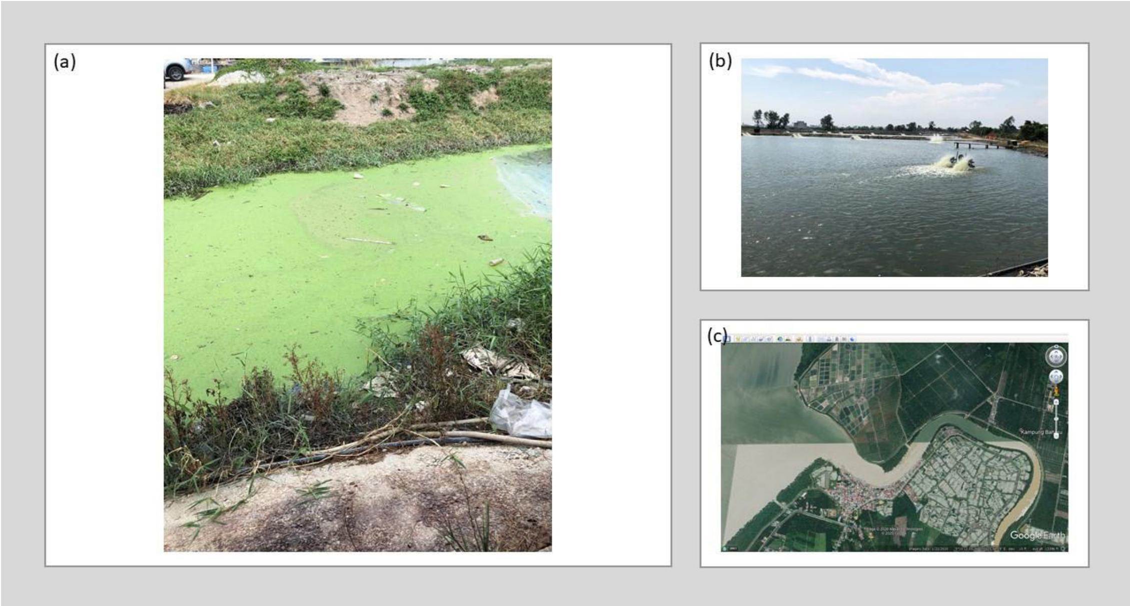

FIGURE 4. (a) The phytoplankton growth in one of the fish ponds; (b) Sungai Udang aquaculture farm and (c) location of Sungai Udang as captured from Google Earth

MAPPING OF AQUACULTURE PONDS IN SG UDANG

As MNDWI showed a higher accuracy than other tested water indices in extracting the aquaculture pond information, the index was applied to the images from 2014 to 2020 for studying the temporal changes of the ponds. Figures 5 and 6 show the spatial and temporal changes of the aquaculture ponds in Sungai Udang, respectively.

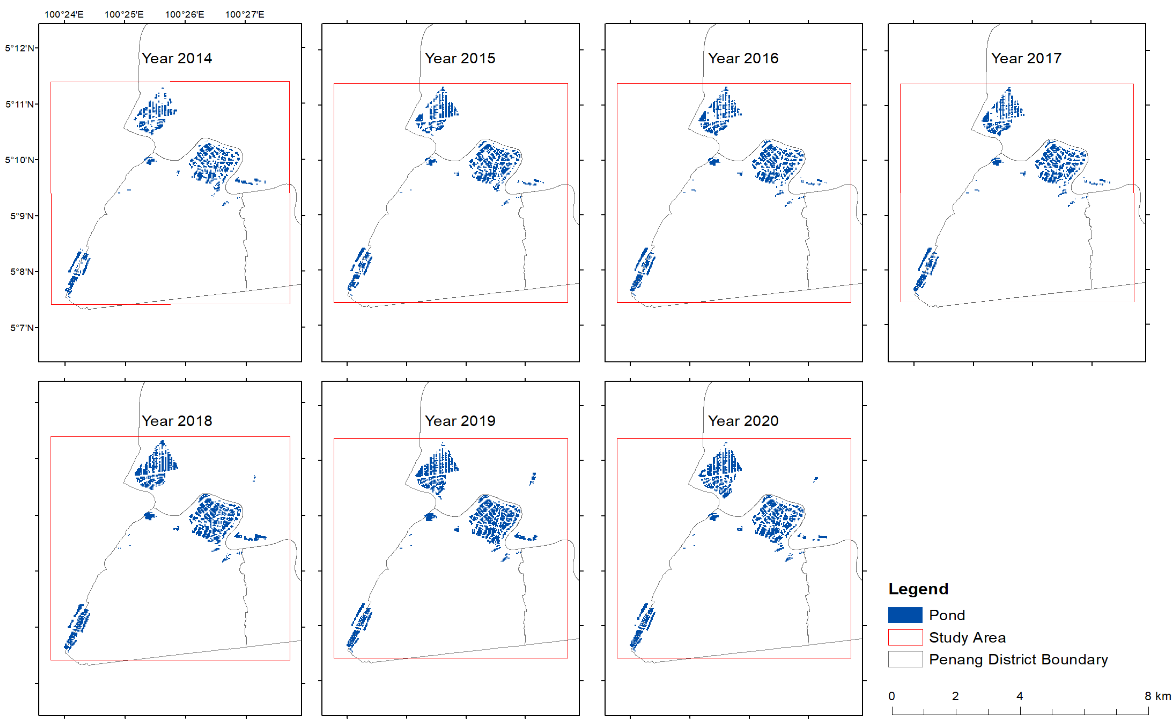

FIGURE 5. (Spatial changes of the aquaculture ponds in Sungai Udang, Pulau Pinang

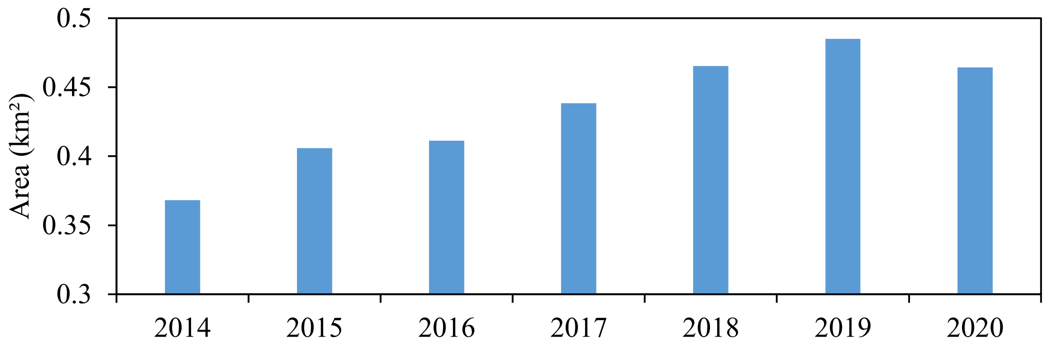

FIGURE 6. Temporal changes of the aquaculture ponds in Sungai Udang, Pulau Pinang from 2014 to 2020

There is a significant expansion of the aquaculture ponds in the study region from 2014 to 2020 as shown in Figures 5 and 6. The expansion of the aquaculture ponds are all inland brackish aquaculture types along the Sungai Udang. The aquaculture ponds have been expanded from 2014 to 2020 by 26.16%, which is equivalent to 96300 m^2. This expansion can be witnessed in all the three clusters of aquaculture ponds.

The expansion of the fishponds is a result from Penang's aquaculture industry advancement drive. In 2015, Penang's aquaculture production achieved the highest revenue in Malaysia, contributing 97,000 metric tons and worth RM1.4 billion of food fish for domestic consumption and exports (Vaghefi 2017). The importance of the aquaculture industry in Penang, envisioned towards sustainable aquaculture that supplies food fish and induced job opportunities to the locals has therefore created future potential to further increase the production in order to meet future market demand. In this case, the current challenges in the aquaculture industry such as pollution and water quality and natural disasters like typhoons and monsoon would need GIS and remote sensing technologies aid to manage the aquaculture ponds better. For example, stakeholders could utilize GIS technology to monitor the water level and quality of the ponds as well as recording the species breed in each pond to better manage the fish feeding practices. Modernization and diversification of agricultural production is one of the targeted aims in the Penang2030 vision that could place Penang as an advanced Green Valley and aquaculture industrial zone.

DISCUSSION

The growth of phytoplankton in the aquaculture ponds as shown in Figure 4(a) may be one of the reasons that contributed to the errors in aquaculture ponds extraction. The band ratioing computation that involves the blue-green reflectance bands is less sensitive towards algal concentrations that live with reflectance colour dissolved organic matters and total suspended matters that existed on the water surfaces (Blondeau-Patissier et al. 2014). In other words, the existence of phytoplankton caused the wavelength absorption and scattering to be lesser than usual, and therefore resulting in lower reflectance recorded (Soja-Woźniaka et al. 2020). Water surface colour captured by satellite in the study region was not the usual colour (Figure 4(c)), where this could somehow have resulted in different spectral reflectance values in the original images.

The growth of phytoplankton in the study region is common because the aquaculture activities induce dissolved organic matter into the water from the fish feed and the waste excretion by the fishes. Without proper waste management and water quality monitoring, especially during the Movement Control Order earlier this year, algal bloom may increase in the aquaculture ponds and affect the ponds extraction using water indices. Another major limitation of this study was the medium spatial resolution of Landsat images, which is 30 m × 30 m per pixel. Landsat images unable to capture the aquaculture pond precisely as the pond size is usually less than one hectare, that covers only a pixel approximately. This spatial resolution limitation also causes difficulty to extract very fine fishpond boundaries. In order to fill this gap, a higher resolution dataset such as Airbus that gave spatial resolution at 50 cm should be used instead. However, high resolution satellite images are costly and sometimes restricted in sharing.

Besides that, integrating radar images, e.g. Sentinel-1, could fill the gap where the broader spectral range and finer spatial resolution shall increase the accuracy of the aquaculture pond mapping, as demonstrated by Sun et al. (2020). The characteristics of radar backscatter that captures surface roughness is efficient in mapping water bodies through filtering of clustered low backscatter values in the image. However, the radar data is only available since 3 April 2014, limiting the study of the aquaculture ponds changes for a longer period.

Conclusion

Mapping aquaculture ponds with remote sensing technology, specifically with band ratioing of multispectral bands, can be advantaged for the fast-growing inland aquaculture industry in Malaysia in terms of geospatial data management. This study presented the use of Landsat 8 bands in extracting aquaculture pond information. The capability of three different water indices, namely Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI) and Automated Water Extraction Index (AWEI), in mapping the aquaculture ponds in Sungai Udang, Pulau Pinang were compared to see the responses of the aquaculture ponds towards each band combination. The results show that MNDWI is the best index for aquaculture ponds extraction in Sungai Udang, with the accuracy of 81.87% and the Kappa coefficient of 0.61, followed by AWEI (accuracy = 61.60% and Kappa coefficient = 0.36) and NDWI (accuracy = 58.21% and Kappa coefficient = 0.33). Then, MNDWI was applied to calculate the spatial changes of aquaculture ponds from 2014 to 2020. The result indicates that the area of aquaculture ponds has expanded by 26.16% since the past seven years. Further research is required to determine the potential spatial distribution changes of aquaculture ponds in the future.

ACKNOWLEDGEMENTS

This project is supported by the Ministry of Higher Education of Malaysia under the Long-term Research Grant Scheme (203/PHUMANITI/67215003). The author would like to thank the editor and reviewers for their constructive comments.

REFERENCES

Amani, M., Ghorbanian, A., Ahmadi, S.A., Kakooei, M., Moghimi, A., Mirmazloumi, S.M., Moghaddam, S.H.A., Mahdavi, S., Ghahremanloo, M., Parsian, S., Wu, Q. & Brisco, B. 2020. Google Earth Engine cloud computing platform for remote sensing big data applications: A comprehensive review. *IEEE Journal in Google Earth Engine for Remote Sensing* 13: 5326-5350.

Aziz, F., Kusratmoko, E. & Mandini, M.D. 2020. Estimation of changes in the lake water level and area using remote sensing techniques (Case study: Lake Toba, North Sumatra). *Proceedings of The International Conference of Science and Applied Geography - IOP Conference. Series: Earth and Environmental Science* 561(012022). pp. 1-7.

Barsi, J.A., Lee, K., Kvaran, G., Markham, B.L. & Pedelty, J.A. 2014. The spectral response of the Landsat-8 operational land imager. *Remote Sensing* 6(10): 10232-10251.

Blondeau-Patissier, D., Gower, J.F.R., Dekker, A.G., Phinn, S.R. & Brando, V. 2014. A review of ocean color remote sensing methods and statistical techniques for the detection, mapping and analysis of phytoplankton blooms in coastal and open oceans. *Progress in Oceanography* 123: 123-144.

Chen, F., Chen, X., Tim, V.d.V., Roberts, D., Jiang, H. & Xu, W. 2020a. Open water detection in urban environments using high spatial resolution remote sensing imagery. *Remote Sensing of Environment* 242(11706): 1-17.

Chen, J., Kang, T., Yang, S., Bu, J., Cao, K. & Gao, Y. 2020b. Open-surface water bodies dynamics analysis in the Tarim River Basin (North-Western China), based on Google Earth Engine cloud platform. *Water* 12(10): 2822-2848.

DeVries, B., Huang, C., Armston, J., Huang, W., Jones, J.W. & Lang, M.W. 2020. Rapid and robust monitoring of flood events using Sentinel-1 and Landsat data on the Google Earth Engine. *Remote Sensing of Environment* 240(111664): 1-15.

Duan, Y., Li, X., Zhang, L., Chen, D., Liu, S. & Ji, H. 2019. Mapping national-scale aquaculture ponds based on the Google Earth Engine in the Chinese coastal zone. *Aquaculture* 520(734666): 1-10.

Duan, Y., Li, X., Zhang, L., Liu, W., Liu, S., Chen, D. & Ji, H. 2020. Detecting spatiotemporal changes of large-scale aquaculture ponds regions over 1988-2018 in Jiangsu Province, China using Google Earth Engine. *Ocean and Coastal Management* 188(105144): 1-11.

FAO. 2020. *The State of World Fisheries and Aquaculture: Sustainability in Action*. Rome: Food and Agriculture Organization of the United Nations.

Feyisa, G.L., Meilby, H., Fensholt, R. & Proud, S.R. 2014. Automated water extraction index: A new technique for surface water mapping using Landsat imagery. *Remote Sensing of Environment* 140: 23-35.

Gao, B.C. 1996. NDWI a normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment* 58(3): 257-266.

Ghorbanian, A., Kakooei, M., Amani, M., Mahdavi, S., Mohammadzadeh, A. & Hasanlou, M. 2020. Improved land cover map of Iran using Sentinel imagery within Google Earth Engine and a novel automatic workflow for land cover classification using migrated training samples. *ISPRS Journal of Photogrammetry and Remote Sensing* 167: 276-288.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D. & Moore, R. 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment* 202: 18-27.

Holben, B. & Justice, C. 1981. An examination of spectral band ratioing to reduce the topographic effect on remotely sensed data. *International Journal of Remote Sensing* 2(2): 115-133.

Ji, L., Zhang, L. & Wylie, B. 2009. Analysis of dynamic thresholds for the normalized difference water index. *Photogrammetric Engineering & Remote Sensing* 75(11): 1307-1317.

Khor, W., Fazhan, H., Ishak, S.D., Kasan, N.A., Liew, H.J., Norainy, M.H. & Ikhwanuddin, M. 2020. Potential impacts of COVID-19 on the aquaculture sector of Malaysia and its coping strategies. *Aquaculture Reports* 18(100450): 1-6.

Koskinen, J., Leinonen, U., Vollrath, A., Ortmann, A., Linquist, E., d'Annunzio, R., Pekkarinen, A. & Käyhkö, N. 2019. Participatory mapping of forest plantations with Open Foris and Google Earth Engine. *ISPRS Journal of Photogrammetry and Remote Sensing* 148: 63-74.

Lim, I. 2015. Something fishy in Kampung Sungai Udang. *Penang Monthly*. https://penangmonthly.com/article/2826/something-fishy-in-kampung-sungai-udang-1.

McFeeters, S.K. 1996. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing* 17(7): 1425-1432.

Nguyen, U.N.T., Pham, L.T.H. & Dang, T.D. 2019. An automatic water detection approach using Landsat 8 OLI and Google Earth Engine cloud computing to map lakes and reservoirs in New Zealand. *Environmental Monitoring and Assessment* 191(4): 235-246.

Soja-Woźniaka, M., Laiolo, L., Baird, M.E., Matear, R. & Clementson, L. 2020. Effect of phytoplankton community size structure on remote-sensing reflectance and chlorophyll *a* products. *Journal of Marine Systems* 211(103400): 1-11.

Sun, Z., Luo, J., Yang, J., Yu, Q., Zhang, L., Xue, K. & Lu, L. 2020. Nation-scale mapping of coastal aquaculture ponds with Sentinel-1 SAR data using Google Earth Engine. *Remote Sensing* 12(18): 3086-3097.

Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S. & Brisco, B. 2020. Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing* 164: 152-170.

Tew, Y.L., Tan, M.L., Narimah, S. & Yang, X. 2019. Urban expansion analysis using Landsat Images in Penang, Malaysia. *Sains Malaysiana* 48(11): 2307-2315.

Vaghefi, N. 2017. Penang's Aquaculture Industry Holds Great Economic Potential. https://penanginstitute.org/publications/issues/1005-penang-s-aquaculture-industry-holds-great-economic-potential/.

Wang, R., Xia, H., Qin, Y., Niu, W., Pan, L., Li, R., Zhao, X., Bian, X. & Fu, P. 2020a. Dynamic monitoring of surface water area during 1989–2019 in the Hetao Plain using Landsat data in Google Earth Engine. *Water* 12(11): 3010-3030.

Wang, Y., Li, Z., Zeng, C., Xia, G.S. & Shen, H. 2020b. An urban water extraction method combining deep learning and Google Earth Engine. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 13: 768-781.

Worden, J. & de Beurs, K.M. 2020. Surface water detection in the Caucasus. *International Journal of Applied Earth Observation and Geoinformation* 91(102159): 1-16.

Xia, Z., Guo, X. & Chen, R. 2020. Automatic extraction of aquaculture ponds based on Google Earth Engine. *Ocean and Coastal Management* 198(105348): 1-10.

Xu, H. 2006. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing* 27(14): 3025-3033.

Yin, Z., Ling, F., Foody, G.M., Li, X. & Du, Y. 2020. Cloud detection in Landsat-8 imagery in Google Earth Engine based on a deep convolutional neural network. *Remote Sensing Letters* 11(12): 1181-1190.

You, N. & Dong, J. 2020. Examining earliest identifiable timing of crops using all available Sentinel 1/2 imagery and Google Earth Engine. *ISPRS Journal of Photogrammetry and Remote Sensing* 161: 109-123.

Yu, Z., Di, L., Rahman, M.S. & Tang, J. 2020. Fishpond mapping by spectral and spatial-based filtering on Google Earth Engine: A case study in Singra Upazila of Bangladesh. *Remote Sensing* 12(17): 2692-2711.

Zhai, K., Wu, X., Qin, Y. & Du, P. 2020. Comparison of surface water extraction performances of different classic water indices using OLI and TM imageries in different situations. *Geo-spatial Information Science* 18(1): 32-42.

Zurqani, H.A., Post, C.J., Mikhailova, E.A., Schlautman, M.A. & Sharp, J.L. 2018. Geospatial analysis of land use change in the Savannah River Basin using Google Earth Engine. *International Journal of Applied Earth Observation and Geoinformation* 69: 175-185.

Yi Lin Tew, Mou Leong Tan, Narimah Samat*, Ngai Weng Chan & Mohd Amirul Mahamud
GeoInformatic Unit, Geography Section
School of Humanities
Universiti Sains Malaysia
11800 USM, Pulau Pinang
Malaysia

Muhammad Azizan Sabjan
Philosophy and Civilization Section
School of Humanities
Universiti Sains Malaysia
11800 USM, Pulau Pinang
Malaysia

Lai Kuan Lee
School of Industrial Technology
Universiti Sains Malaysia
11800 USM, Pulau Pinang
Malaysia

Kok Fong See
School of Distance Education
Universiti Sains Malaysia
11800 USM, Pulau Pinang
Malaysia

Seow Ta Wee
Faculty of Management Technology and Business
Universiti Tun Hussein Onn
86400 Batu Pahat, Johor Darul Takzim
Malaysia

*Corresponding author; email: narimah@usm.my

Received: 26 March 2021
Accepted: 12 June 2021