

## MONITORING 15-YEAR LAND USE/LAND COVER CHANGE IN THE VIETNAMESE MEKONG DELTA

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### Article history

Received: 07/01/2021; Received in revised form: 04/08/2021; Accepted: 08/09/2021

### Abstract

*Although land use/land cover (LULC) information plays a critical role in the maintenance of living standards with a balance among the environment, development, and sustainability, it remains little comprehensive understanding in the entire Vietnamese Mekong Delta (VMD). In this study, we used the random forest algorithm, Landsat images, ancillary and empirical reference data to carefully analyse the 15 years' spatiotemporal changes (2005 - 2020) of LULC in the VMD region. Results show that agriculture has been the most dominant land, accounting for approximately half of the whole region during the fifteen years. Remarkably, most of the LULC categories have undergone dramatic transformation with the proportion of the wetland area decreasing from about 16% in 2005 to 5% in 2020, whereas that of the aquaculture area sharply increased from about 12% to 19% over the same period. Meanwhile, there was a marked increase in the area of perennial crops and built-up lands. These results of LULC maps and change detection helps understand the impact of past policies and the role of several factors such as socio-economic trends and environmental changes in this region.*

**Keywords:** *Agricultural expansion, landsat images, land use/land cover changes, Mekong delta, wetland change*

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DOI: <https://doi.org/10.52714/dthu.11.5.2022.985>

Cite: Nguyen Ho, Phan Van Phu, and Nguyen Thi Hong Diep. (2022). Monitoring 15-year land use/land cover change in the Vietnamese Mekong Delta. *Dong Thap University Journal of Science*, 11(5), 93-103.

# 15 NĂM QUAN TRẮC SỰ THAY ĐỔI LỚP PHỦ BỀ MẶT ĐẤT/SỬ DỤNG ĐẤT TẠI VÙNG ĐỒNG BẰNG SÔNG CỬU LONG, VIỆT NAM

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## Lịch sử bài báo

Ngày nhận: 07/01/2021; Ngày nhận chỉnh sửa: 04/08/2021; Ngày duyệt đăng: 08/09/2021

## Tóm tắt

Mặc dù những thông tin liên quan đến sử dụng đất/lớp phủ bề mặt đất (LULC) đóng một vai trò quan trọng trong việc duy trì mối cân bằng giữa môi trường, phát triển và bền vững, nhưng nó vẫn còn ít được hiểu rõ cho toàn vùng Đồng bằng sông Cửu Long, Việt Nam (VMD). Trong nghiên cứu này, chúng tôi sử dụng thuật toán rừng ngẫu nhiên, hình ảnh vệ tinh Landsat, dữ liệu tham khảo phụ trợ và thực nghiệm để phân tích cẩn thận những thay đổi về mặt không gian của LULC tại VMD trong vòng 15 năm qua (2005 - 2020). Kết quả nghiên cứu cho thấy rằng đất nông nghiệp là lĩnh vực chiếm ưu thế nhất - khoảng một nửa diện tích toàn vùng trong suốt 15 năm. Đáng chú ý, phần lớn các loại LULC này đã có sự chuyển đổi mạnh mẽ với tỷ trọng diện tích đất ngập nước giảm từ khoảng 16% năm 2005 xuống còn 5% năm 2020, trong khi diện tích đất dành cho nuôi trồng thủy sản tăng mạnh từ khoảng 12% lên 19% so với cùng kỳ. Trong khi đó, diện tích đất trồng cây lâu năm và đất xây dựng cũng được ghi nhận gia tăng rõ rệt. Những kết quả của bản đồ LULC và những phát hiện biến động có thể được sử dụng nhằm giúp tìm hiểu tác động của các chính sách trong quá khứ cũng như vai trò của một số yếu tố như xu hướng phát triển kinh tế xã hội và những thay đổi môi trường tại VMD.

**Từ khóa:** Mở rộng nông nghiệp, ảnh vệ tinh Landsat, biến động lớp phủ bề mặt/sử dụng đất, Đồng bằng sông Cửu Long, mất đất ngập nước.

## 1. Introduction

Coastal deltas are fundamental to human beings due to their numerous advantages such as a diversity of natural resources as well as ecosystem services, but they are also considered as fragile ecosystems (Kelletat *et al.*, 2005; Moder *et al.*, 2012). The socio-economic development and agricultural intensification are altering the delta's ecosystems, followed by possible negative impacts on society and the environment. The evidence of these adverse effects can be clearly seen in the Vietnamese Mekong Delta (VMD), which plays an important role in the agricultural and aquaculture production for the country. Although this region accounts for only 12% of Vietnam's natural land area, it supplies a great percentage of the country's agricultural products, for example, approximately 50% of rice for domestic use, up to 90% of exported rice, 65% of aquaculture, 70% of fruits, and 60% of exported fish (GSO, 2019). These processes are closely linked to the exploitation of natural resources, thus holding substantial implications for the region's rural landscapes (Duong *et al.*, 2001; Kelletat *et al.*, 2005).

While land use/land cover (LULC) information is widely adopted to support sustainable development and policy decisions (Castella *et al.*, 2007; Nguyen Hong Quan *et al.*, 2020), its role is not sufficiently acknowledged in the environmental management in the VMD. In fact, there are global and regional LULC products ranging from coarse to medium resolutions, which cover the entire region. Well-known examples of coarse resolution LULC maps are IGBP (Global Land Cover Characterization), UMD (UMD Global Land Cover Facility), and GlobCover 2009 (Global Land Cover Maps). However, such a coarse spatial resolution LULC is unlikely to accurately reflect the complex agricultural landscape in the VMD. In addition, previous studies have attempted to detect and describe LULC change for small areas or only certain regions, but not for the entire delta (Funkenberg *et al.*, 2014; Ngo *et al.*, 2020; Tran *et al.*, 2021). Another noteworthy point is that many studies have focused mainly on a particular LULC, namely the characterization and quantification of rice crop (Kontgis *et al.*, 2015), wetlands (Nguyen Ho. *et al.*, 2020), aquaculture and mangroves (Vo *et al.*, 2013),

involving little information on the full dominant LULC characteristics. A LULC with few classes has been conducted on the entire VMD by (Liu *et al.*, 2020), but they combined agriculture, orchards and perennial plants into a single class, missing important classes such as open water. Hence, more up-to-date geospatial information about landscape changes of the entire delta is essential for better understanding changes at the earth's surface and the successful modelling and simulation of the potential impact of changed drivers.

Supervised classification methods are more effective in identifying complex land cover classes compared to unsupervised approaches, if detailed a-priori knowledge of the study area and good training data exist (Cihlar, 2000). In supervised classification methods, among algorithms, new evidence suggests that the Random Forest algorithm is considered one of the best machine-learning classifiers for large-scale LULC mapping (Maxwell *et al.*, 2018). Moreover, study region's road network has been improved significantly in recent years, available accessing the remote areas of the region to create ground truth data and interview local people for better understanding the land-use status quo (or the surface features of the region) as well as the driving forces of LULC change. With that idea in mind, this study employs Random Forest theory to propose an estimate of LULC change based on empirical evidence extracting from onsite data and local knowledge for the entire VMD.

Therefore, this study aims: (1) to create the two-milestone accurate LULC maps (2005 and 2020) for the entire VMD using Random Forest algorithm and (2) to shortly analyze the LULC change from 2005 to 2020 in the entire delta.

## 2. Materials and Methods

### 2.1. Study area

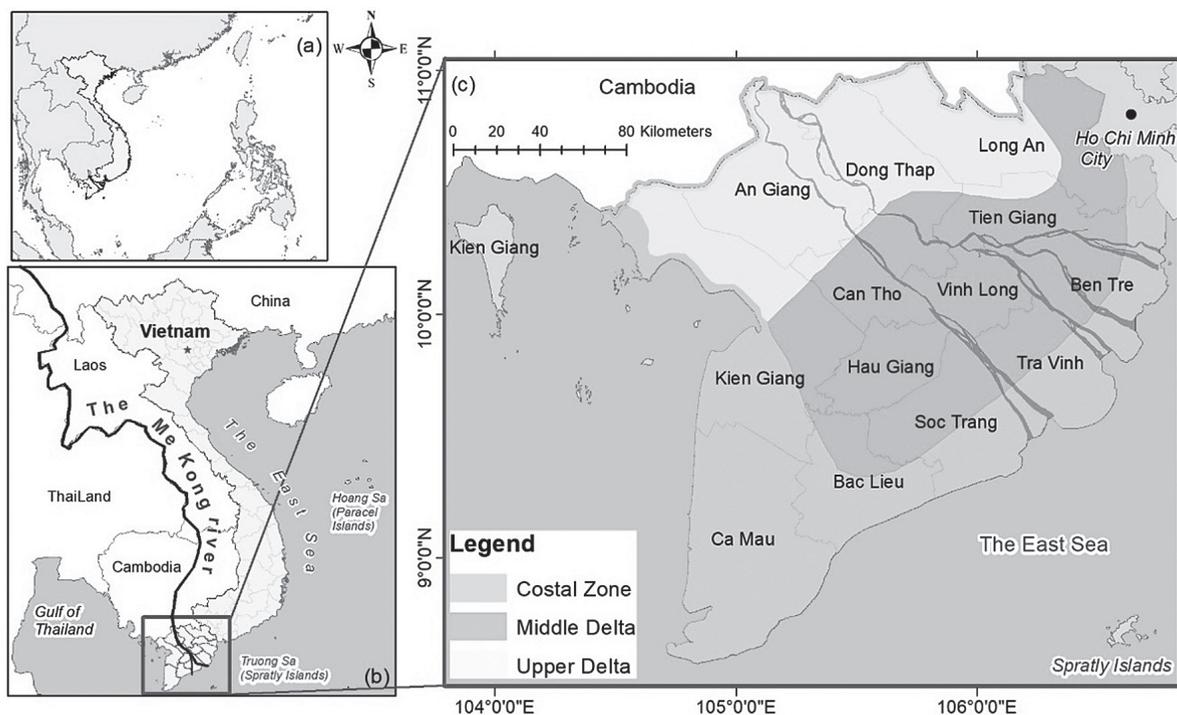
The Vietnamese Mekong Delta (VMD) located between 8°33' - 10°55'N and 104°30' - 106°50'E, in the South-West of Vietnam. The region, known as the Nine Dragon (Cuu Long) river delta, is the home of approximately 20 million inhabitants and described as a vast triangular plain of about 40,000 square kilometers, stretching from the Cambodia-Vietnam border to the East Sea of Vietnam. The VMD is

administratively divided into 13 provinces with Can Tho city as the center of the delta (Fig. 1).

The topography of the VMD is relatively flat, ranging from one to two meters above the sea level. Its climate is affected by the East-Asian seasonal monsoon and characterized by two yearly seasons: the rainy season from May to November and the dry one from December to April. Annual precipitation varies between 1,800 and 2,300 mm, mainly distributed in

the rainy season, while it is warm whole year with the annual average temperature being around 27°C.

LULC is diverse and dynamic in the VMD, dominantly covered by various agricultural lands, wetlands, fruit trees, and mangroves. In recent decades, the Government (Vietnam) has promoted agriculture and aquaculture production, causing a major conversion among LULC types (Mekong Delta Plan, 2013; Nguyen Hong Quan *et al.*, 2020).



**Figure 1.** The location of Vietnam in the South East Asia (a); the location of the study area in Vietnam (b), and three sub-regions of the Mekong delta (c, modified from Mekong Delta Plan, 2013)

## 2.2. Data acquisition and processing

Landsat imagery was the main data collection as considering the change-detection comparability of this long-term study with other previously useful results. Given that the VMD is very cloudy, it is impossible to collect single cloud-free images covering the full delta. We, therefore, used multi-season images to not merely address the problems of missing data but also improve the accuracy of land cover classifications due to the presence of phenological vegetation conditions (Rodriguez-Galiano *et al.*, 2012). For the year 2020, this study used Landsat 8 Operational Land Imager (OLI); Landsat 7 Enhanced Thematic Mapper Plus (ETM+)

and Landsat 5 Thematic Mapper (TM) for the year 2005. These data were collected from the Earth Explorer (U.S. Geological Survey). All scenes were geo-referenced to a Universal Transverse Mercator map projection (UTM zone 48N), WGS84 ellipsoid, and datum. Validation data were collected during field surveys in 2020, from high-resolution satellite images (Quickbird and Worldview images available via GoogleEarthTM), and from ancillary datasets. These image pre-processing tasks were executed by the support of Geospatial Data Abstraction Library (GDAL), a library by the Open Source Geospatial Foundation (information available at [www.gdal.org/gdal.pdf](http://www.gdal.org/gdal.pdf)).

**Table 1. The useful information of Landsat bands used in this study**

<b>Data/sensor</b>	<b>Band No</b>	<b>Wave length (<math>\mu\text{m}</math>)</b>	<b>Spatial resolution (m)</b>	<b>Description</b>
Landsat 8	Band 1	0.435-0.451	30	Coastal / Aerosol
	Band 2	0.452-0.512	30	Blue
	Band 3	0.533-0.590	30	Green
	Band 4	0.636-0.673	30	Red
	Band 5	0.851-0.879	30	NIR
	Band 6	1.566-1.651	30	SWIR1
	Band 7	2.107-2.294	30	SWIR2
	Band 10	10.6-11.9	100	TIRS 1
	Band 11	11.5-12.51	100	TIRS2
Landsat 5/7	Band 1	0.441-0.514	30	Blue
	Band 2	0.519-0.601	30	Green
	Band 3	0.631-0.692	30	Red
	Band 4	0.772-0.898	30	NIR
	Band 5	1.547-1.749	30	SWIR1
	Band 7	2.064-2.345	30	SWIR2
	Band 6	10.31-12.36	60	TIRS1

### 2.3. Classification scheme

The number and typology of LULC categories were defined based on field work, available land use statistics, expertise, and consideration of the previous studies about LULC of the delta (Funkenberg *et al.*, 2014; Le Thuy Ngan *et al.*, 2018; Nguyen Thanh

Son *et al.*, 2013), and exploratory analysis of satellite data with unsupervised classification. Accordingly, an eight-category LULC classification scheme was designed, namely agriculture, aquaculture, perennial crops, wetlands, upland forest, mangrove forest, built-up area, and open water (Table 2).

**Table 2. Brief description of the land use/land cover categories of the study area**

LULC type	Code	Description
Agriculture	AG	Rice paddy, seasonal cropland
Wetlands	WL	Melaleuca forests, seasonally inundated grasslands
Perennial crops	PC	Fruit trees, trees in the residential areas and other perennial plants
Built-up area	BA	Residential areas, and barren lands
Aquaculture	AQ	Fish and shrimp ponds and other aquaculture farms
Open water	OW	Rivers, canals and reservoirs
Upland forest	UF	Natural/planting Forest located in the upland areas
Mangroves	MA	Mangrove forest in coastal areas

#### 2.4. Classification processing and accuracy assessment

Random forest algorithm is an ensemble learning method employing a large number of classifiers or decision trees (Breiman, 2001). It is widely applied for classification and regression due to its outperformance and robustness of its rivals (Maxwell *et al.*, 2018). Among methods to generate LULC maps, Random forest is popular due to its high accuracy in classification (Maxwell *et al.*, 2018). In this study, we classified each cloud-free optical data set separately using a random forest classification. After that, each separately classified image was combined to generate the final maps. After classification, two LULC maps had been filtered by 3 x 3 kernel majority filters to minimize the “salt-and-pepper effect” before validating and performing change detection. LULC changes occurring between 2005 and 2020 were assessed via post-classification map comparisons (Coppin *et al.*, 2004). Post-classification processing was done in QGIS version 3.4.

We assessed classification accuracy by generating stratified random points for the classified images. We used the data from field trips and high-resolution images available on GoogleEarth™, Bing™ for both periods as the ground truth information. Contingency tables of the reference data and remote sensing-based classification were produced, the overall accuracy, user’s accuracy (commission error), producer’s accuracy (omission error) and Kappa coefficient were calculated (Congalton & Green, 2009).

### 3. Results and discussion

#### 3.1. LULC classification

Two eight-category land use/land cover products were generated for the VMD in the years of 2005 and 2020 (Fig.2). The overall accuracy of the two maps was from 90% to 91% with the Kappa coefficient in the range of 87% to 88%, respectively. In the two products, the agriculture (2005) and upland forest (2020) obtained the highest precision, while wetland had the lowest accuracy. The detail of confusion matrix is shown in Table 3, 4.

**Table 3. Confusion matrix of 2005 LULC map. UA: Users' accuracy (%); PA: Producers' accuracy (%); Ka: Kappa coefficient; AG: Agriculture; WE: Wetlands; PC: Perennial crops; BU: Built-up area; AQ: Aquaculture; OP: Open Water; UF: Upland Forest; MA: Mangroves**

2005		Predicted category									
		AG	WE	PC	BU	AQ	OP	UF	MA	Total	PA (%)
Actual category	AG	875	13	9	5	25	0	2	0	929	94.2
	WE	14	255	9	1	15	13	0	18	325	78.5
	PC	8	11	513	0	7	0	10	15	564	91.0
	BU	8	4	7	223	2	1	0	3	248	90.0
	AQ	4	15	7	1	236	2	0	6	271	87.1
	OW	2	0	2	2	8	245	0	6	265	92.5
	UF	0	8	0	0	0	0	77	0	85	90.6
	MA	0	12	18	0	0	12	8	264	314	84.1
	Total	911	318	565	232	293	273	97	312	3001	
	UA (%)	97	80.2	90.8	96.2	80.6	89.8	79.4	84.7		89.6
Ka	0.09	0.01	0.04	0.01	0.01	0.01	0.00	0.01	0.18	0.87	

**Table 4. Confusion matrix of 2020 LULC map. UA: Users' accuracy (%); PA: Producers' accuracy (%); Ka: Kappa coefficient; AG: Agriculture; WE: Wetlands; PC: Perennial crops; BU: Built-up area; AQ: Aquaculture; OP: Open Water; UF: Upland Forest; MA: Mangroves**

2020		Predicted category									
		AG	WE	PC	BU	AQ	OP	UF	MA	Total	PA (%)
Actual category	AG	1020	1	18	7	5	0	0	0	1051	97.1
	WE	11	312	26	1	4	0	0	31	385	81.1
	PC	7	17	725	6	1	2	0	1	759	95.6
	BU	20	2	31	303	4	5	2	0	367	82.6
	AQ	7	0	0	2	245	15	0	10	279	87.9
	OW	25	1	7	11	38	234	0	2	318	73.6
	UF	1	1	0	0	0	0	42	0	44	95.5
	MA	0	6	1	0	1	0	0	252	260	97.0
	Total	1091	340	808	330	298	256	44	296	3463	
	UA (%)	94	91.8	89.8	91.9	82.3	91.5	95.5	85.2		90.6
Ka	0.10	0.01	0.05	0.01	0.01	0.01	0.00	0.01	0.19	0.88	

Overcoming the challenges of dense cloudy contamination, a time-series random-forest-based method was proposed to produce two eight-category LULC classification (2005 and 2020) in the VMD, using the high temporal frequency of Landsat images, spectral indices, and ancillary data. The performance of remote-sensing-based mapping can be significantly improved with support of ground-truth data and ancillary data. Also, onsite images, local knowledge and experts' advice supply useful insights into this land cover mapping, instead of using singly visual interpretation. A number of previous studies on the LULC mapping of the VMD rely mainly on the visual

interpretation of high spatial resolution satellite data such as Google Earth images for validating that may cause errors (McRoberts *et al.*, 2018). For example, Liu *et al.*, 2020 created a series of seven LULC maps of the VMD from 1979 to 2015 based on mainly visual interpretation of Google Earth images. These results seem to be essential for a long-term analysis of land cover dynamics. This study, however, detected serious errors in these products based on our results and field surveys. That is, one km away from the coastal line, coconut and fruit trees were misclassified as mangrove at a large area.

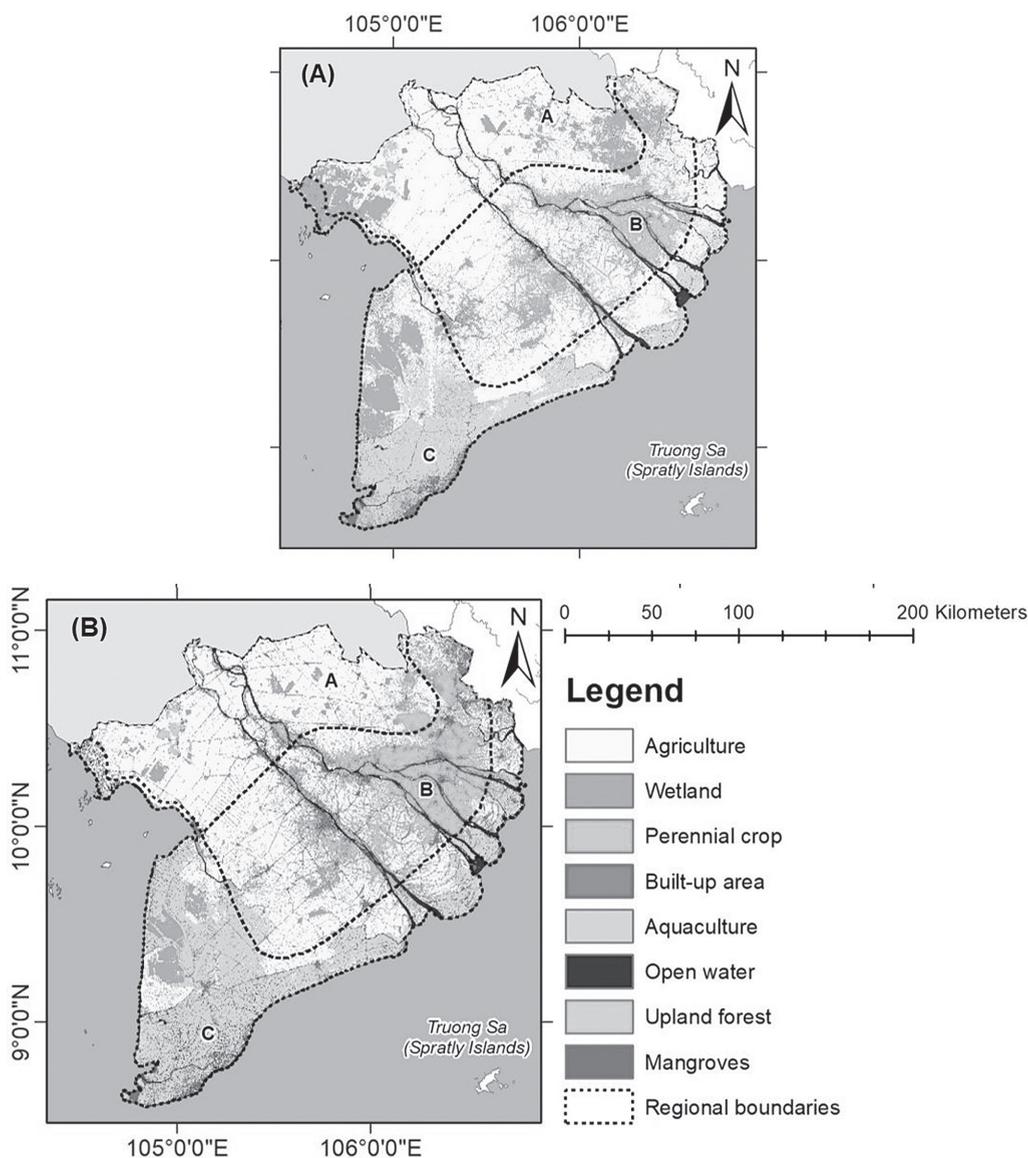


Figure 2. Inland LULC maps of the VMD for the years 2005 (A); and 2020 (B)

### 3.2. LULC change in the VMD

Agriculture is still the dominant LULC type, covering nearly 50% of the total delta although the area of agricultural land has relatively decreased in the last fifteen years. The area of agriculture sharply decreased from 21,858 km<sup>2</sup> in 2005 to 18,569 km<sup>2</sup> in 2020. Other significant change is the rapid loss of wetland (Fig. 3). Over the last 15 years, approximately 70% of wetland has lost across the entire VMD (more than 4.400 km<sup>2</sup>). On the other hand, built-up and aquaculture areas significantly increased at the same period. In particular, the area of built-up gained by 1837 km<sup>2</sup>, and aquaculture areas dramatically increased by more than 2400 km<sup>2</sup> in 2020 (Fig. 3). Remarkably, perennial crops areas nearly doubled over the fifteen years (from 3806 km<sup>2</sup> to 6765 km<sup>2</sup>).

Post-classification change detection analysis showed that the LULC transformation of the VMD varied according to local sub-regional areas and LULC types. For instance, agricultural areas converted rapidly into aquaculture land type in coastal areas characterized by brackish environment, whereas perennial crops increased considerably along the Tien and Hau rivers and in the North East of the VMD. Nevertheless, agriculture remained the most popular LULC type in the flood plain regions, for instance, Plain of Reeds (Đồng Tháp Mười) and Long Xuyen Quadrangle (Tứ giác Long Xuyên) (Fig. 2). These findings are in agreement with previous studies reporting a noticeable interrelation between land-use dynamics and changing in hydrological regimes across the entire VMD (Le Thuy Ngan *et al.*, 2018).

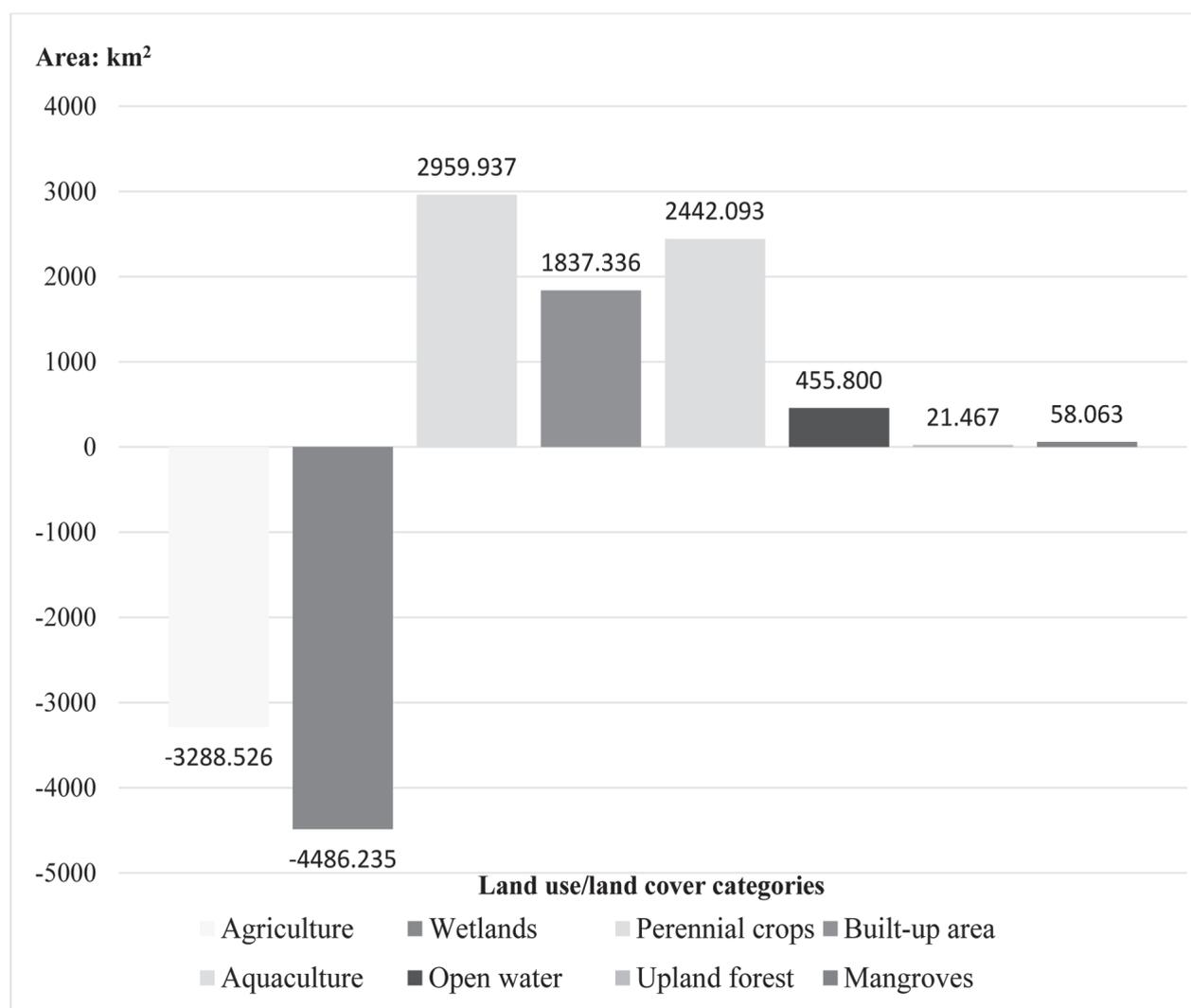


Figure 3. Gain/loss of LULC types in the period 2005-2020 (in km<sup>2</sup>)

## 5. Conclusion

This study provided the detailed of two years LULC mapping results at a spatial resolution of 30 m with an overall accuracy range around 90% and studied the LULC change during the period from 2005 to 2020 for the entire VMD. Using the Random Forest algorithm, Landsat images, ancillary and empirical reference data, our study overcomes the major challenges of extremely cloudy contamination to generate eight-category LULC products, including agriculture, aquaculture, perennial crops, wetlands, upland forest, mangrove forest, built-up area, and open water. Generally, wetland and agricultural areas declined while aquaculture, perennial crops, and settlements increased between 2005 and 2020. The largest observed transition featured aquaculture growth in place of wetlands and rice fields. The highest observed net changes in LULC types were agriculture, followed by wetlands. In addition, there has been a substantial increase in the area of built-up lands with sparse built-up areas near the canal and river systems. The main driving forces of changes are expected to be anthropogenic activities with a series of policy promulgations and the rapid population growth in the VMD over the last two decades. This understanding of LULC change status contributes to modelling the evolution of LULC patterns, thereby providing policy makers with a better adjustment to future land use plans in the VMD.

**Acknowledgments:** The authors are grateful to the U.S. Geological Survey (<http://glovis.usgs.gov>) for providing the Landsat data. We also would like to thank Mr. Phan Cao Duong and Mr. Ta Hoang Trung for their technical support./

## References

- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5-32. <https://doi.org/10.1023/A:1010933404324>.
- Castella, J.-C., Pheng Kam, S., Dang Dinh Quang, Verburg, P. H., & Thai Hoanh, Chu (2007). Combining top-down and bottom-up modelling approaches of land use/cover change to support public policies: Application to sustainable management of natural resources in northern Vietnam. *Land Use Policy*, 24(3), 531-545. <https://doi.org/10.1016/j.landusepol.2005.09.009>.
- Cihlar, J. (2000). Land cover mapping of large areas from satellites: Status and research priorities. *International Journal of Remote Sensing*, 21(6), 1093-1114. <https://doi.org/10.1080/014311600210092>.
- Congalton, R. G., & Green, K. (2009). *Assessing the accuracy of remotely sensed data: principles and practices* (2nd ed.). Boca Raton: CRC Press/Taylor & Francis.
- Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Digital change detection methods in ecosystem monitoring: a review. *International Journal of Remote Sensing*, 25(9), 1565-1596. <https://doi.org/10.1080/0143116031000101675>.
- Duong Van Ni, Safford, R. J., & Maltby, E. (2001). Environmental change, ecosystem degradation and the value of wetland rehabilitation in the Mekong Delta. In W. N. Adger (Ed.), *Living with Environmental Change* (122-136). London: Routledge. <https://doi.org/10.4324/9780203995570>.
- Funkenberg, T., Tran Thai Binh, Moder, F., & Dech, S. (2014). The Ha Tien Plain - wetland monitoring using remote-sensing techniques. *International Journal of Remote Sensing*, 35(8), 2893-2909. <https://doi.org/10.1080/01431161.2014.890306>.
- GSO, (General Statistical Office). (2019). *Statistical Yearbook of Vietnam 2018*. Ha Noi: Statistical Publishing House.
- Kelletat, D., Chen, J., Rybczyk, J. M., Penland, S., Kulp, M. A., Duedall, I. W., et al. (2005). Deltaic Ecology. In M. L. Schwartz (Ed.), *Encyclopedia of Coastal Science* (359-362). Dordrecht: Springer Netherlands.
- Kontgis, C., Schneider, A., & Ozdogan, M. (2015). Mapping rice paddy extent and intensification in the Vietnamese Mekong River Delta with dense time stacks of Landsat data. *Remote Sensing of Environment*, 169, 255-269. <https://doi.org/10.1016/j.rse.2015.08.004>.
- Le Thuy Ngan, Bregt, A. K., van Halsema, G.

- E., Hellegers, P. J. G. J., & Nguyen, Lam Dao. (2018). Interplay between land-use dynamics and changes in hydrological regime in the Vietnamese Mekong Delta. *Land Use Policy*, 73, 269-280. <https://doi.org/10.1016/j.landusepol.2018.01.030>.
- Liu, S., Li, X., Chen, D., Duan, Y., Ji, H., Zhang, L., *et al.* (2020). Understanding Land use/Land cover dynamics and impacts of human activities in the Mekong Delta over the last 40 years. *Global Ecology and Conservation*, 22, e00991. <https://doi.org/10.1016/j.gecco.2020.e00991>.
- Maxwell, A. E., Warner, T. A., & Fang, F. (2018). Implementation of machine-learning classification in remote sensing: an applied review. *International Journal of Remote Sensing*, 39(9), 2784-2817. <https://doi.org/10.1080/01431161.2018.1433343>.
- McRoberts, R. E., Stehman, S. V., Liknes, G. C., Næsset, E., Sannier, C., & Walters, B. F. (2018). The effects of imperfect reference data on remote sensing-assisted estimators of land cover class proportions. *ISPRS Journal of Photogrammetry and Remote Sensing*, 142, 292-300. <https://doi.org/10.1016/j.isprsjprs.2018.06.002>.
- Mekong Delta Plan, (MDP). (2013). *Mekong Delta Plan: Long-term vision and strategy for a safe, prosperous and sustainable delta*. Vietnam-Netherlands Co-operation. Retrieved from: <https://www.mekongdeltaplan.com/library/documents>.
- Moder, F., Kuenzer, C., Xu, Z., Leinenkugel, P., Quyen, B. Van, Renaud, F. G., & Kuenzer, C. (2012). The Mekong Delta System. In Renaud F.G. and Kuenzer C. (Eds), *The Mekong Delta System: Interdisciplinary Analyses of a River Delta*, (133-165). Dordrecht: Springer Netherlands.
- Ngo Duc Khanh, Lechner, A. M., & Vu Tuong Thuy (2020). Land cover mapping of the Mekong Delta to support natural resource management with multi-temporal Sentinel-1A synthetic aperture radar imagery. *Remote Sensing Applications: Society and Environment*, 17, 100272. <https://doi.org/10.1016/j.rsase.2019.100272>.
- Nguyen Ho, Phan Van Phu, Nguyen Thi Phuong, Lu Ngoc Tram Anh, Nguyen Thi Hai Ly, & Nguyen Thi Hong Diep (2020). Wetland monitoring in the Plain of Reeds using Landsat images. *Journal of Science Natural Science*, 65(3), 194-204. <https://doi.org/10.18173/2354-1059.2020-0022>.
- Nguyen Hong Quan, Tran Duc Dung, Dang K. Khoi, Korbee, D., Pham, L. D. M. H., Vu, L. T., *et al.* (2020). Land-use dynamics in the Mekong delta: From national policy to livelihood sustainability. *Sustainable Development*, 28(3), 448-467. <https://doi.org/10.1002/sd.2036>.
- Nguyen Thanh Son, Chen, C. F., Chen, C. R., Huynh Ngoc Duc, & Chang, L. Y. (2013). A phenology-based classification of time-series MODIS data for rice crop monitoring in Mekong Delta, Vietnam. *Remote Sensing*, 6(1), 135-156. <https://doi.org/10.3390/rs6010135>.
- Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 67, 93-104. <https://doi.org/10.1016/j.isprsjprs.2011.11.002>.
- Tran Van Thuong, Tran Duy Xuan, Nguyen Ho, Latorre-Carmona, P., & Myint, S. W. (2021). Characterising spatiotemporal vegetation variations using LANDSAT time-series and Hurst exponent index in the Mekong River Delta. *Land Degradation & Development*, 32(13), 3507-3523. <https://doi.org/10.1002/ldr.3934>.
- Vo Quoc Tuan, Oppelt, N., Leinenkugel, P., & Kuenzer, C. (2013). Remote Sensing in Mapping Mangrove Ecosystems - An Object-Based Approach. *Remote Sensing*, 5(1), 183-201. <https://doi.org/10.3390/rs5010183>.