Doi: 10.31276/VJSTE.61(1).74-81

Remote sensing applications for analysing the impacts of land cover changes on the upper part of the Dong Nai river basin

Hung Pham[1, 2*], Van Trung Le[2], Le Phu Vo[2]

[1]Department of Natural Resources and Environment, Lam Dong province

[2]Ho Chi Minh city University of Technology - Vietnam National University, Ho Chi Minh city

Received 10 October 2018; accepted 3 January 2019

Abstract:

In recent years, activities related to socio-economic development have led to land cover (LC) changes in the upper part of the Dong Nai river basin. The use of remote sensing applications to analyse the impacts of these changes plays an important role in the managing the sustainability of the river basin. This paper introduces a solution for analysing the impacts of LC changes on the water balance in the upstream catchment of the Dong Nai river in Lam Dong province. Landsat images were used for mapping and monitoring major changes over the last 20 years. Rainfall and water discharge data was collected from the local hydrometeorological stations to identify the impacts of the LC changes on the runoff in the catchment area. The results show that the forest area was reduced by more than 223,576 ha (23%). The main changes were an increase in the agricultural area from 18.2 to 31.3% and in water bodies from 0.9 to 2.2%. The latter was due to hydropower development projects in the catchment area. The LC changes caused by the changes in the hydrological conditions of the river basin have had a significant impact on water resources. The identification of the main LC changes in the catchment area could be useful for establishing a policy to protect the headwater forests and mitigate against future impacts.

Keywords: **hydrological conditions, land cover change, Landsat images, remote sensing, upper part of Dong Nai river basin.**

Classification number: **4.1**

Introduction

Land cover (LC) is the physical material on the Earth's surface, and LC maps play an important role in Earth system studies and ecosystem management [1]. Land cover changes can be related to natural processes, such as flooding and erosion, and anthropogenic activities, including urbanization and agriculture. Annually updated LC information is valuable for formulating socio-economic development policies and as data for environmental management applications, such as vulnerability and risk assessment [2]. Characterising and mapping LC is essential for multiple purposes, including planning and managing natural resources (e.g. land or water resource development, flora and fauna conservation), modelling environmental variables, and understanding the spatial distribution of habitats. Remote sensing and digital image processing enable observation, mapping, monitoring, and assessment of LC to be conducted at a range of spatial and temporal scales [3].

Remote sensing provides comprehensive thematic maps based on an image classification for visual or computer-aided analysis to assess past LC changes [4]. The choice of classification algorithm depends on many factors, including ease of use, speed, scalability, the interpretability of the classifier, the kind of data, the statistical distribution of classes and target accuracy. Unsupervised classification is typically used when limiting the knowledge and availability of the LC types [5, 6].

Clustering algorithms, including k-mean and ISODATA, run iteratively until convergence of an optimal set of clusters is achieved. Post-classification refinement techniques, such as merging and splitting clusters, are necessary before labeling because automatically produced

*Corresponding author: Email: hungmtk25@yahoo.com

clusters do not necessarily correspond with LC types [7, 8]. Parametric supervised classifiers are typically used when expert knowledge and the availability of the LC types are sufficient. However, supervised classification with algorithms, such as maximum likelihood, minimum distance, and discriminant analysis, is difficult to perform with multi-temporal data containing many spectral features and multi-modal distributions [9]. Other approaches involve various classifiers used in parallel or in succession, which can be either supervised or unsupervised [10]. Nonparametric classifiers, such as k-nearest neighbours (kNN), decision trees (DT), neural networks (NN), support vector machines (SVM), random forests (RF), and hierarchical classification based on multi-source and multi-temporal data and geo-knowledge (HC-MMK), impose boundaries of arbitrary geometries and provide higher flexibility although they involve computationally intense iterative processes [11]. Nonparametric classifiers that focus on decision rules of class boundaries are more suitable when the statistics and distribution of LC types are unknown [12].

Change image production uses post-classification change detection technique through cross-tabulation [13]. The success of this technique depends on the reliability of the maps created using image classification. Large-scale changes such as the construction of new hydroelectric reservoirs or major urban development might be mapped reasonably easily, whereas for evolutionary changes, such as erosion, colonization and degradation, the boundaries may be indistinct and the class-labels uncertain [14].

Land use and land cover (LULC) changes alter the hydrological system and can have potentially significant effects on water resources [15]. In addition, the impact of LULC change on watershed hydrology are interlinked with climate change impacts [16].

According to the People's Committee of Lam Dong Province [17], the forest area of Lam Dong was 513,529 ha in 2014 and accounted for 52.5% of the provincial area. This report indicates that the forest area was reduced around 8% in 10 years. However, in the upper part of Dong Nai (UPDN), most of which belongs to Lam Dong province, historical LC change has yet to be examined in detail. In order to analyse past LC changes that impact upon the flow regime in the river basin in 10-year intervals (1994, 2004, and 2014), a changes detection technique was applied using a supervised maximum likelihood classification (MLC) algorithm. The impact of LC change on the flow regime in the UPDN river basin was assessed largely using hydrometeorological data collected along with Landsat images. The objectives of this study are to create LC maps and to observe LC changes over a 20-year period (1994-2014). In order to achieve these objectives, investigations were conducted into the effects of past LC changes and the effects of these changes on water discharges in the downstream part of the river basin. Specifically, the impact of headwater forest change and hydropower development on the flow regime in the UPDN was assessed.

Study area

The study area is located in the UPDN river basin (Fig. 1), which covers an area of 972,460 ha and belongs to the provinces of Lam Dong, Dak Nong, and Dong Nai. The upstream catchment area of the Dong Nai River has a

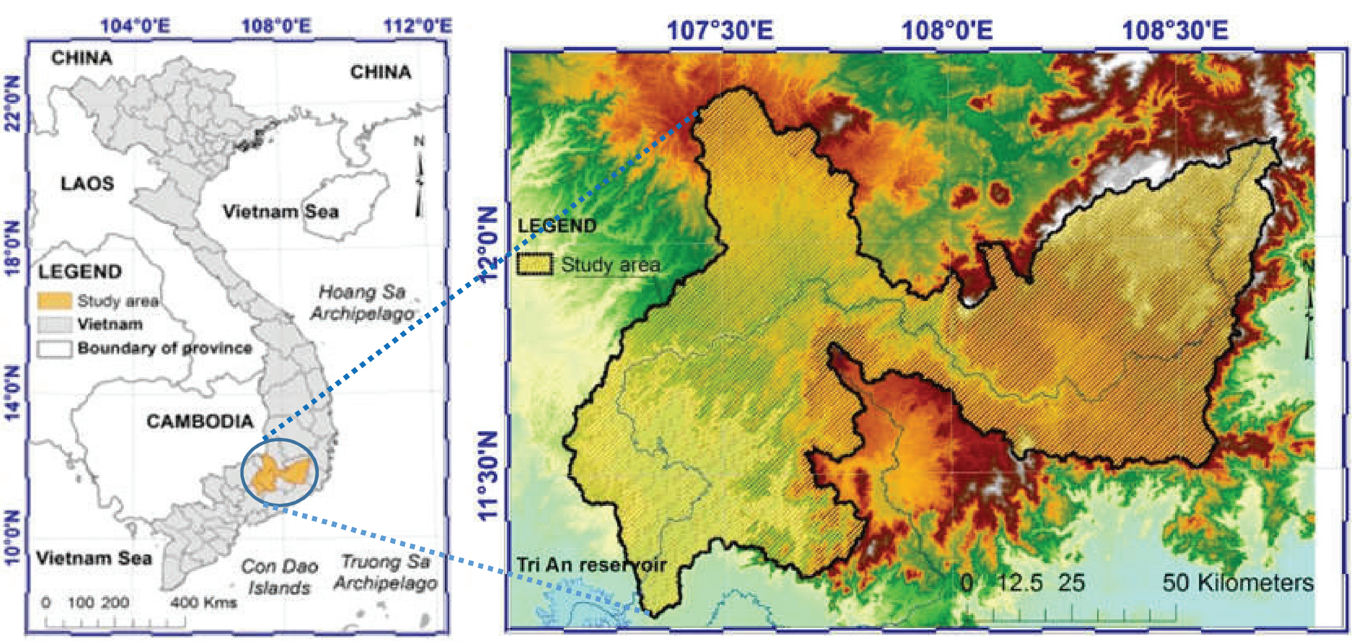

Fig. 1. Location of the upper part of Dong Nai river basin.

tropical wet climate with two seasons: the rainy season from May to November and the dry season from December to April. Over the past 33 years from 1981-2014, the average annual temperature was 22^{0}C, annual precipitation was 2,500 mm, and annual humidity was 83% [18]. Forest cover is found mainly at high elevations in the West and North. The agricultural areas are characterised by small fields generally in close proximity to rivers.

Materials and methods

Landsat data

Image data from Landsat-5 TM (1994, 2004) and Landsat-8 OLI/TIRS (2014) covering the study area was downloaded from the United States Geological Survey (USGS) website (http://earthexplorer.usug.gov), as summarized in Table 1. The criteria for the selection were that cloudless images be available and that the data be collected at a ground measurement station (Ta Lai gauge).

Table 1. Characteristics of Landsat images.

Year	Image	Landsat_Scene_ID	Resolution	Date_Acquired
1994	Landsat-5 TM	LT51240521994007BKT00	30x30 m	1994-01-07
2004	Landsat-5 TM	LT51240522004355BKT01	30x30 m	2004-12-20
2014	Landsat-8 OLI/TIRS	LC81240522014030LGN01	30x30 m	2014-01-30

Geometric correction

The original sub-scenes of Landsat images comprised of a significant among of bands data, which was combined into one image (6 bands) by function layer stacking using ENVI 4.5 software. For this study, geometric correction was carried out using a ground control point from the available maps (Topographic maps of Lam Dong province in 2010, scale 1:100,000) to geocode the 2014 image. This image was then used to register the images from 2004 and 1994. The geometric correction was done by calculating the root mean square error (RMSE) between the two images, which was less than 0.2 pixels. Corrected geometric images were then cut (subset) into the UPDN river basin.

Training sample data

Training sample data was used to create an LC map with seven main classes, which are listed in Table 2.

Table 2. Land cover classes of the study area.

Type of LC	Description
(1) Water bodies	Natural (Lakes, Rivers, etc.) or man-made water bodies (e.g. Reservoirs)
Forest (2) *Broadleaf evergreen forest* (3) *Mixed forest* (4) *Coniferous forest*	All forests: evergreen broadleaf forest, coniferous forest (pine), mixed forest (bamboo and broadleaf forests, pine, and broadleaf forest, etc.)
(5) Built-up residential areas	Residential areas, roads and built-up
(6) Seasonal agricultural land	Rice fields, soybean, potato
(7) Perennial agricultural land	Rubber, coffee, tea, etc.

The training sample data was created based on the GIS data, the land use map of the area (provincial land use planning maps for the period 2010-2020), and the vector data for polygons of training sample data, so-called region of interest (ROI) is used in classification method of MLC. In addition, Google Earth images were deployed to support the selection of LC types for the training sample polygons by integrating Arc Google Tool with ArcGIS 10.1.

The result of the LC classification was evaluated based on ground truth data collected at test sites. The error matrix was used to indicate the quality of LC classifications in 1994, 2004, and 2014. Three natural forest classes (broadleaf evergreen forest, mixed forest, coniferous forest) were combined came under the definition of forest for the purposes of assessing LC changes. This meant that seven classes were categorized into five main classes: water bodies, forest areas, built-up residential areas, seasonal agricultural land, and perennial agricultural land [19, 20].

Land cover classification

The maximum likelihood pixel-based classification method is the most commonly used technique for Landsat images [21]. This study used the MLC method for Landsat 5 TM and Landsat-8 OLI/TIRS. The accuracy assessment is reflected by overall accuracy and Kappa coefficient in which overall accuracy included user's accuracy and producer's accuracy.

The thematic map used to analyse LC change trends in the UPDN river basin is shown in Fig. 2. The LC map was created using images from (A) Landsat-5 TM 1994, (B) Landsat-5 TM 2004 and (C) Landsat-8 OLI/TIRS 2014. The area for each type of LC in the river basic and the cover percentages in are summarised in Tables 3-5.

Results and discussion

Image classification: supervised classification was carried out using MLC, and the same training data was used for each image. This proved an efficient solution for the visualisation of LC in the basin. The results indicate that the average forest cover decreased from 72.68% of the river basin area in 1994 to 49.97% in 2014. This finding can assist managers in undertaking further analysis regarding forest cover change trends with the aim of achieve sustainable development in the UPDN river basin.

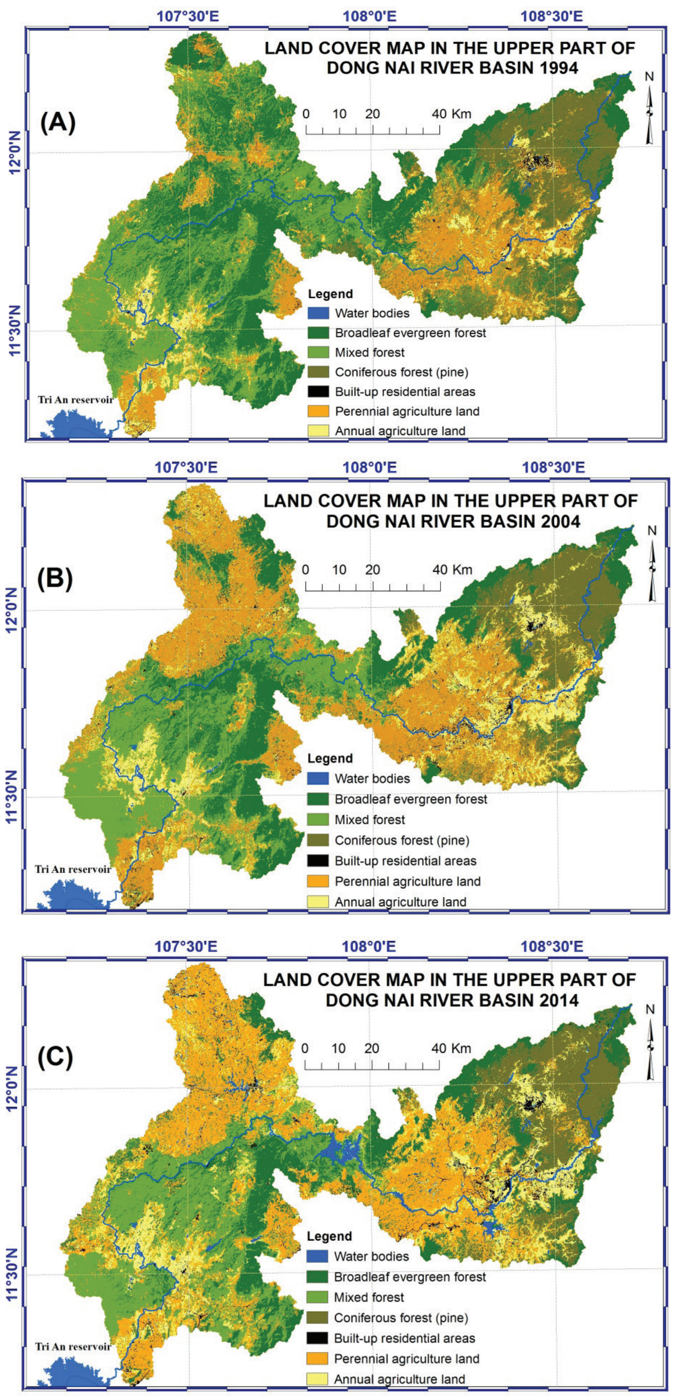

Fig. 2. Land cover map created using different images: (**A**) Landsat-5 TM 1994, (**B**) Landsat-5 TM 2004, (**C**) Landsat-8 OLI/TIRS 2014.

Table 3. Area of land cover and cover percentage (1994).

Types of Land cover	Area (ha)	Percentage (%)
Water bodies	8,505	0.87
Forest areas	706,803	72.68
- Broadleaf evergreen	*283,257*	*29.13*
- Mixed forest	*283,616*	*29.16*
- Coniferous forest	*139,930*	*14.39*
Built-up residential	7,922	0.81
Seasonal agricultural	177,033	18.20
Perennial agricultural	72,197	7.42
Total	972,460	100.00

Table 4. Area of land cover and cover percentage (2004).

Types of Land cover	Area (ha)	Percentage (%)
Water bodies	8,557	0.88
Forest areas	520,359	53.51
- Broadleaf evergreen	*188,318*	*19.37*
- Mixed forest	*219,435*	*22.56*
- Coniferous forest	*112,606*	*11.58*
Built-up residential	19,305	1.99
Seasonal agricultural	292,927	30.12
Perennial agricultural	132,312	13.61
Total	972,460	100.00

Table 5. Area of land cover and cover percentage (2014).

Types of Land cover	Area (ha)	Percentage (%)
Water bodies	21,590	2.22
Forest areas	485,908	49.97
- Broadleaf evergreen	*178,720*	*18.38*
- Mixed forest	*194,050*	*19.95*
- Coniferous forest	*113,138*	*11.63*
Built-up residential	24,274	2.50
Seasonal agricultural	304,231	31.28
Perennial agricultural	136,457	14.03
Total	972,460	100.00

Classification accuracy assessment: an assessment of the quality of LC classifications in 1994, 2004 and 2014 indicated that all seven classifications have very good overall accuracy (77.7-87%). In all cases, the Kappa coefficient had a high value (0.74-0.85). The user's accuracy and producer's accuracy for the LC maps are shown in Table 6. Therefore, the thematic map was used to analyse LC change trends and their impacts on the regime flow in the UPDN river basin.

The results show that the highest accuracy was for water bodies and the lowest accuracy was for broadleaf evergreen forest (Prod. = 57.02, 67.28, and 74.40% for 1994, 2004, and 2014, respectively).

Table 6. Summary of classification accuracy for the land cover map in 1994, 2004 and 2014.

Class name	1994		2004		2014	
	User (%)	*Prod. (%)*	*User (%)*	*Prod. (%)*	*User (%)*	*Prod. (%)*
Water bodies	98.26	98.64	98.10	99.95	97.88	98.90
Broadleaf evergreen forest	90.38	57.02	94.53	67.28	86.85	74.40
Mixed forest	65.54	87.19	74.53	89.89	71.01	87.74
Coniferous forest	91.42	92.52	96.47	97.93	94.65	95.62
Built-up residential areas	70.51	81.55	92.94	93.89	91.95	78.04
Seasonal agricultural land	89.69	79.35	92.84	76.73	90.20	80.90
Perennial agricultural land	69.03	90.51	80.82	92.62	77.77	84.94
Overall accuracy (OA)	77.7%		87.0%		84.3%	
Kappa	0.74		0.85		0.81	

This result can be explained by the fact that the river basin is partially covered by areas with high-density coffee trees, causing confusion between broadleaf forest and perennial agricultural land. Furthermore, the user's accuracy for the mixed forest class was also low (user = 65.5, 74.53, and 71.01%, for 1994, 2004, and 2014, respectively). This can be attributed to the fact that the Landsat images were taken in the dry season, when spectral signatures of mixed forest pixels are most similar to measured perennial plant spectra. Moreover, the accurate classification was a good match with the land use planning maps of Lam Dong province for the periods of 2000-2010 and 2010-2020 [22, 23].

Detection change: to analyse LC change, three natural forest classes (broadleaf evergreen forest, mixed forest, and coniferous forest) were grouped under the forest definition and thematic maps containing five main LC classes were created. The LC map for 1994 was overlaid onto the LC map for 2014 in order to identify the regions where major changes had occurred in the five LC classes between 1994 and 2014.

The results show that the for 1994, 2004, and 2014 the forest area occupied 706,803 ha (72.68%), 520,359 ha (53.51%), and 485,908 ha (49.97%), respectively. This means that the area of forest coverage changed significantly over the 20 years from 1994 to 2014. This result is consistent with trends reported by the UN (2005) for the period 1990-2000, during which tropical forests in South-East Asia were reduced from 53.9% in 1990 to 48.6% in 2000 [24]. However, the forest area did not change much between 2004 and 2014, only dropping from 53.51% (2004) to 49.97% (2014), as shown in Tables 3-5.

In contrast, there was a significant increase of seasonal agricultural land and perennial agricultural land in the 10 years from 1994 to 2004. This indicates that the demand for agricultural land increased due to local socio-economic development. The area of seasonal agricultural land was 177,033 ha (18.20%) in 1994, 292,927 ha (30.12%) in 2004, and 304,231 ha (31.28%) in 2014, whereas perennial agricultural land accounted for 72,197 ha (7.42%) in 1994, 132,312 ha (13.61%) in 2004, and 136,457 ha (14.03%) in 2014.

The area of water bodies fluctuated over the study period measuring 8,505 ha (0.87%) in 1994, 8,557 ha (0.88%) in 2004, and 21,590 ha (2.22%) in 2014. This fluctuation can be explained by many reasons including climate conditions (change in annual rainfall), water use and land use change. The increase in the area covered by water bodies in the period 2004-2014 also reflects the recent construction of the large hydropower plants Dai Ninh (300 MW), Da Dang 2 (34 MW), Dong Nai 3 (180 MW), Dong Nai 4 (340 MW), Dong Nai 2 (70 MW) and Dong Nai 5 (150 MW), which came into operation in 2008, 2009, 2010, 2012, 2013, and 2014, respectively [18, 25].

Residential coverage was 7,922 ha (0.81%) in 1994, 19,305 ha (1.99%) in 2004, and 24,274 ha (2.50%) in 2014. This reflects the low levels of urbanisation and population growth in the basin.

Table 7 summarises the results of the changes in area for each LC class during the period from 1994 to 2014.

Table 7. Cross-tabulation of land cover classes between 1994 and 2014 (area in ha).

		1994						
		Water	*Forest*	*Built-up*	*Perennial Agri.*	*Seasonal Agri.*	*Row Total*	*Class Total*
2014	*Water*	5,122	11,484	147	5,210	2,769	24,732	24,733
	Forest	895	448,091	414	25,976	7,877	483,253	483,309
	Built-up	200	11,202	2,435	14,092	5,794	33,722	33,743
	Perennial Agri.	464	168,920	1,431	91,231	16,821	278,875	278,885
	Seasonal Agri.	1,821	67,188	3,493	40,462	38,920	151,885	151,912
	Class Total	8,502	706,885	7,919	176,972	72,182	-	-
	Class Changes	3,382	259,168	5,488	85,830	33,282	-	-
	Image Difference	16,231	**-223,576**	25,824	101,913	79,730	-	-

Notes: The 'Class Total' row shows the total number of pixels in each initial state class. The 'Class Total' column shows the total number of pixels in each final state class. The 'Row Total' column is a class-by-class summation of all final state pixels that fell into the selected initial state classes. The 'Class Changes' row shows the total number of initial state pixels that changed classes. The 'Image Difference' row is the difference between the total number of equivalently classed pixels in the two images, computed by subtracting the initial state class total from the final state class total.

Overall, the results show that the area of the forest cover decreased by 223,576 ha from an average cover of 72.68% of the natural area in 1994 to 49.97% in 2014. The agricultural land area and water surface (bodies) area also increased in the same period due to the construction of the hydropower reservoirs.

Figure 3 shows major changes from forest to other land classes in the river basin.

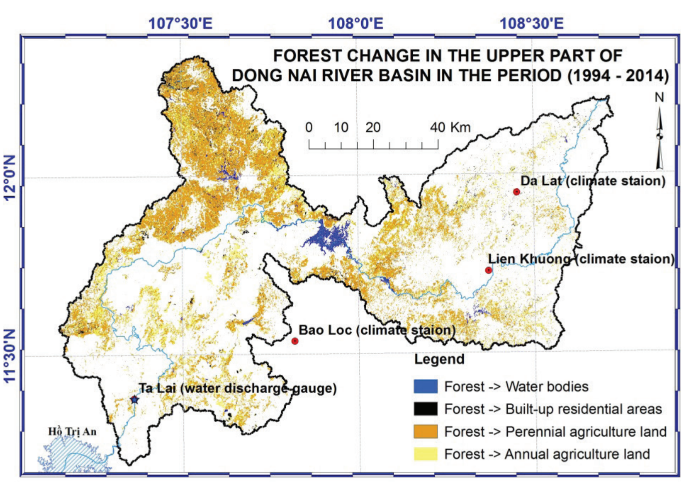

Fig. 3. Changes of forest into other land classes during the period from 1994 to 2014.

Land cover change impacts: in order to analyse the impacts of LC changes on the water balance in the upstream catchment area of the Dong Nai river, the difference between the area of each LC type must be assessed. Table 7 shows that the area of forest in the UPDN river basin was reduced by 223,576 ha (22.99%) over the 20-year period 1994-2014 due to the conversion of forests into built-up, perennial agricultural, and seasonal agricultural land. The changes for these LC types can be explained by a decrease in the level of evapotranspiration in the river basin. The increase in the area of water bodies caused by the recent development of hydropower projects had an impact on evapotranspiration and the annual water balance of the catchment in the dry season due to an increase in water consumption caused by irrigation practices. In this study, the impact of LC changes on hydrology can be analysed on water discharges in the river basin that affects the downstream part of the Dong Nai river to serve the local socio-economic development. In order to identify the impact of LC change on water discharges in the river basin, rainfall data was collected from three weather stations (Da Lat, Lien Khuong, Bao Loc) and discharge data was collected from Ta Lai gauge, as shown in Fig. 3. The hydrometeorological data was collected along with the Landsat images in 1994, 2004, 2014. The yearly rainfall and yearly discharge total for Ta Lai gauge is shown in Fig. 4.

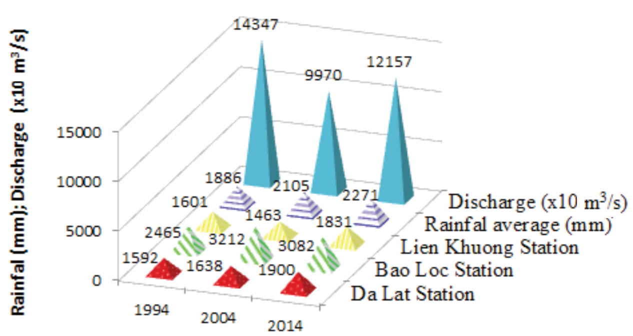

Fig. 4. Yearly rainfall at three weather stations and yearly discharge total at Ta Lai gauge.

The distribution of the mean monthly rainfall for the three climate stations and the monthly discharge are shown in Figs. 5, 6. Obviously, the average rainfall for the three meteorological stations did not change significantly, but the total runoff at the downstream part of the river basin changed dramatically in 2014. The flow in the dry season of year 2014 is higher than it was in 1994. At the same time, water discharges in the river basin for the 2014 rainy season were lower than those in 1994. This can be explained by the hydropower operations in the river basin. For example, water transportation for the Dai Ninh hydropower (300 MW) plant reduced the total water discharge in the lower river.

This is evidence that land use change influenced the flow regime in the river. These findings provide local managers with information on natural resources and environmental management practices to protect headwater forests.

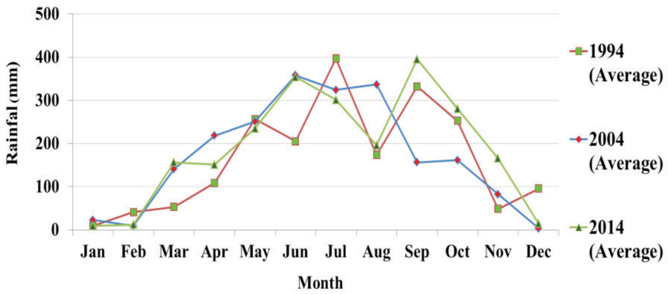

Fig. 5. Monthly rainfall average from three weather stations in 1994, 2004, and 2014.

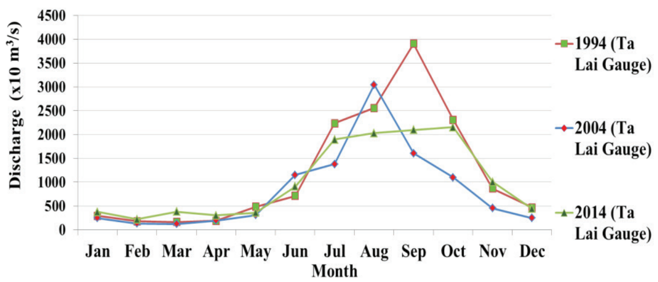

Fig. 6. Monthly discharge observed at Ta Lai gauge in 1994, 2004, and 2014.

Conclusions

The study results show that using Landsat images with algorithm of maximum likelihood supervised classification (MLC) together with generally available data is a comprehensive approach for analysing the impacts of LC changes on the UPDN river basin. The analysis of these results shows that forest area was reduced by more than 223,576 ha (23%) over the 20 years from 1994 to 2014. The agricultural area increased from 18.2% to 31.3% and water bodies also increased from 0.9% to 2.2% due to hydropower development projects in the catchment area. These results indicate that the LC changes were caused by changes in the hydrological conditions of the river basin, which have a significant impact on water resources.

The average rainfall at the three meteorological stations did not change significantly but the total runoff at the downstream part of the river basin changed dramatically in 2014. Land cover change and cascade hydroelectric reservoirs are the major causes of erratic river flow regimes. These changes have had a negative effect on the water quality of the Dong Nai river.

The findings are useful for informing management practices in the watershed area. An analysis of future LC changes and their impacts on the UPDN river basin based on high resolution images would be helpful for the creation of the suitable solutions to the sustainable watershed management.

ACKNOWLEDGEMENTS

The authors would like to thank Ho Chi Minh city University of Technology, Vietnam National University, Ho Chi Minh city, and the Department of Natural Resources and Environment of Lam Dong province for supporting this study.

The authors declare that there is no conflict of interest regarding the publication of this article.

REFERENCES

[1] P. Gong, J. Wang, L. Yu, Y. Zhao, Y. Zhao, L. Liang, Z. Niu, X. Huang, H. Fu, S. Liu, Congcong Li, X. Li, W. Fu, C. Liu, Y. Xu, X. Wang, Q. Cheng, L. Hu, W. Yao, H. Zhang, P. Zhu, Z. Zhao, H. Zhang, Y. Zheng, L. Ji, Y. Zhang, H. Chen, A. Yan, J. Guo, L. Yu, L. Wang, X. Liu, T. Shi, M. Zhu, Y. Chen, G. Yang, P. Tang, B. Xu, C. Giri, N. Clinton, Z. Zhu, J. Chen, and J. Chen (2013), "Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data", *International Journal of Remote Sensing*, **34(7)**, pp.2607-2654.

[2] C. Gomez, J.C. White, and M.A. Wulder (2016), "Optical remotely sensed time series data for land cover classification: a review", *ISPRS Journal of Photogrammetry and Remote Sensing*, **116**, pp.55-72.

[3] J. Rogon and D.M. Chen (2004), "Remote sensing technology for mapping and monitoring land cover and land use change", *Progress in Planning*, **61**, pp.301-325.

[4] G.M. Foody (2002), "Status of land cover classification accuracy assessment", *Remote Sensing of Environment*, **80**, pp.185-201.

[5] Y. Chen and P. Gong (2013), "Clustering based on eigenspace transformation - CBEST for efficient classification", *ISPRS Journal of Photogrammetry and Remote Sensing*, **83**, pp.64-80.

[6] H.D. Eva, A.S. Belward, E.E.D. Miranda, C.M.D. Bella, V.R. Gond, O.T.H. Er, S.J. Ones, M. Sgrenzaroli, and S. Fritz (2004), "A land cover map of South America", *Global Change Biology*, **10**, pp.731-744.

[7] M.A. Wulder, J.C. White, M. Granny, H.J. Hall, J.E. Luther, A. Beaudoin, D.G. Goodenough, and J.A. Dechka (2008), "Monitoring Canada's forest, part 1: completion of the EOSD land cover project", *Can. J. Remote Sensing*, **34(6)**, pp.549-562.

[8] T.R. Loveland, B.G. Reed, J.F. Brown, D.O. Ohlen, Z. Zhu, L. Yang, and J.W. Merchant (2000), "Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data", *International Journal of Remote Sensing*, **21**, pp.1303-1330.

[9] H. Glanz, L. Carvalho, D. Sulle-Menashe, and M.A. Friedl (2014), "A parametric model for classifying land cover an evaluating training data based on multi-temporal remote sensing data", *Journal of Photogrammetry and Remote Sensing*, **97**, pp.219-228.

[10] J. Chen, A. Liao, X. Cao, L. Chen, X. Chen, C. He, G. Han, S. Peng, M. Lu, W. Zhang, X. Tong, and J. Mills (2014), "Global land cover mapping at 30 m resolution: a POK-based operational approach", *Journal of Photogrammetry and Remote Sensing*, **103**, pp.7-27.

[11] G. Lei, A. Li, J. Bian, Z. Zhang, H. Jin, X. Nan, W. Zhao, J. Wang, X. Cao, J. Tan, Q. Liu, H. Yu, G. Yang, and W. Feng (2016), "Land cover mapping in Southwestern China using the HC-MMK approach", *Remote Sensing*, **8(4)**, pp.1-22.

[12] G.M. Foody and A. Mathur (2006), "The use of small training sets containing mixed pixels for accurate hard image classification: training on mixed spectral responses for classification by a SVM", *Remote Sensing of Environment*, **103**, pp.179-189.

[13] A. Shalaby and R. Tateishi (2007), "Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the Northwestern coastal zone of Egypt", *Applied Geography*, **27**, pp.28-41.

[14] G.M. Foody and D.S. Boyd (1999), "Detection of partial land cover change associated with the migration of inner-class transitional zones", *International Journal of Remote Sensing*, **20**, pp.2723-2740.

[15] P.D. Wagner, S. Kumar, and K. Schneider (2013), "An assessment of land use change impacts on the water resources of the Mula and Mutha rivers catchment upstream of Pune, India", *Hydrology and Earth System Sciences*, **16**, pp.2233-2246.

[16] L.M. Mango, A.M. Melesse, M.E. McClain, D. Gann, and S.G. Setegn (2011), "Land use and climate change impacts on the hydrology of the upper Mara river basin, Kenya: results of a modeling study to support better resource management", *Hydrology and Earth System Sciences*, **15**, pp.2245-2258.

[17] People's Committee of Lam Dong province (2015), *Decision No. 299/QD-UBND dated 28/1/2015 on reporting the results of forest investigation of Lam Dong province in 2014*, Da Lat, Lam Dong, Vietnam.

[18] Statistical Bureau of Lam Dong province (2015), *Statistical Yearbook of Lam Dong province*, Da Lat, Lam Dong, Vietnam.

[19] Y. Zhao, P. Gong, L. Yu, L. Hu, X. Li, C. Li, H. Zhang, Y. Zheng, J. Wang, Y. Zhao, Q. Cheng, C. Liu, S. Liu, and X. Wang (2014), "Towards a common validation sample set for global land-cover mapping", *International Journal of Remote Sensing*, **35**, pp.4795-4814.

[20] V.D. Sy, M. Herold, F. Achard, R. Beuchle, J.G.P.W. Clevers, E. Lindquist, and L. Verchot (2015), "Land use pattern carbon losess following deforestation in South America", *Environmental Research Letters*, **10**, pp.1-15.

[21] D. Phiri and J. Morgenroth (2017), "Developments in landsat land cover classification methods: a review", *Remote Sensing,* **9(967)**, pp.1-25.

[22] Government of Vietnam (2003a), *Land use planning map the period of 2000-2010 of Lam Dong province*, Ha Noi, Vietnam.

[23] Government of Vietnam (2013b), *Land use planning map the period of 2010-2020 of Lam Dong province*, Ha Noi, Vietnam.

[24] UN (2005), *World and regional trends*, Millennium Indicators Databases.

[25] Department of Natural Resources and Environment of Lam Dong province (2013), *Report 456/BC-STNMT dated 11/28/2013 on hydropower development projects in Lam Dong province*, Da Lat, Lam Dong, Vietnam.