LAND-COVER DYNAMICS IN SOUTHEAST ASIA: CONTRIBUTION OF OBJECT-ORIENTED TECHNIQUES FOR CHANGE DETECTION

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ABSTRACT:

Land-cover changes occur at unprecedented rates in tropical ecosystems of Southeast Asia, threatening the high biodiversity of this region. To monitor such important changes, remote sensing techniques are increasingly used at different spatial scales. In this study, we investigate land-cover changes at landscape level over a twenty-year period in seven sites located in Cambodia, Lao People's Democratic Republic (Lao PDR) and Thailand.

For each site we acquired high spatial resolution scenes from SPOT satellites at three dates from 1987 to 2008, as well as Digital Elevation Models (SPOT and SRTM DEMs). An object-oriented changes detection method was applied to the images to assess for each site *i)* the location and *ii)* the rate of land-cover changes. We also computed synthetic landscape indices from the classified objects, reflecting two main aspects of landscape ecology: fragmentation and landscape heterogeneity.

The multi-temporal analysis of contrasted landscapes put into evidence the difficulty to implement a unique classification process including numerous object-related indices. Nevertheless, object-oriented classification techniques applied on SPOT imagery were appropriate to map the land-cover on the different study areas, allowing the analysis of land-cover changes. Our study highlighted different spatio-temporal patterns of land-cover changes among the study sites. According to our results, annual deforestation rates ranged from 0.65% to 1.84%, the highest changes rates being observed in Cambodia and Lao PDR. Moreover, fragmentation indices revealed disparities in the dynamics of habitat fragmentation between the three countries. Methods, results and perspectives of this work are discussed.

RÉSUMÉ:

Les écosystèmes tropicaux d'Asie du Sud-Est connaissent des changements d'occupation du sol sans précédent, constituant une menace pour la forte biodiversité de cette région. Afin de suivre de tels changements, la télédétection est de plus en plus utilisée à différentes échelles spatiales. Nous étudions ici les changements d'occupation du sol sur une période de vingt ans, à l'échelle du paysage de sept sites d'études localisés au Cambodge, au Laos et en Thaïlande.

Pour chaque site, des images à haute résolution spatiale des satellites SPOT ont été acquises à trois dates entre 1987 et 2008, ainsi que des Modèles Numériques de Surface (SPOT et SRTM DEMs). Une méthode orientée-objet de détection des changements a été appliquée à ces images pour évaluer pour chaque site d'étude *i)* la localisation et *ii)* le taux de changement d'occupation du sol. A partir des objets classifiés, nous avons également calculé des indices paysagers synthétiques reflétant la fragmentation et l'hétérogénéité du paysage.

Cette analyse multi-temporelle a mis en évidence la difficulté de mettre en place un processus unique de classification comprenant de nombreux indices pour des paysages contrastés. Cependant, les techniques de classification orientées objet se sont avérées appropriées pour cartographier l'occupation du sol des différentes zones d'études, et ainsi d'en étudier les changements. Les résultats mettent en évidence différents motifs de changements d'occupation du sol, avec des taux annuels de déforestation compris entre 0,65 et 1,84 %, les changements les plus importants étant observés au Cambodge et au Laos. Par ailleurs, les indices de fragmentation révèlent des disparités entre les trois pays. Les méthodes, résultats et perspectives de ce travail sont discutés.

1. INTRODUCTION

In Southeast Asia, the high biodiversity (Myers *et al.*, 2000) is threatened by rapid and recent habitat modifications. The highest deforestation rate is observed there compared to other regions (Achard *et al.*, 2002). This is likely to lead to massive species declines and extinctions (Sodhi *et al.*, 2004). In this context, remote sensing techniques are valuable tools for landscape change monitoring at different spatial scales, and are increasingly used (Chowdhury, 2006).

This paper investigates land-cover changes at landscape level over a twenty-year period in Cambodia, Lao People's Democratic Republic and Thailand. Seven sites were chosen along a North-South gradient. An object-oriented changes detection method was applied to SPOT satellite imagery to assess for each site *i)* the location and *ii)* the rate of land-cover changes.

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2. METHODOLOGY

2.1 Study sites and satellite images

The seven study sites were chosen along the Mekong River (Figure 1) in the frame of the CERoPath project (www.ceropath.org). For each site we acquired high spatial resolution satellite images at three dates from 1987 to 2008 (Table 2). Spatial and spectral resolutions depend on the available SPOT scenes. When possible, cloud-free scenes (*i.e.* from the dry season) were chosen. The most recent scene for each site had a pixel size of 2.5 x 2.5 meters in panchromatic mode and 10 x 10 meters in multispectral mode. SPOT-Digital Elevation Models (DEM) with a spatial resolution of 20 x 20 meters together with the SRTM (Shuttle Radar Topography Mission, http://srtm.usgs.gov/) DEM (90 meters spatial resolution) were also acquired.

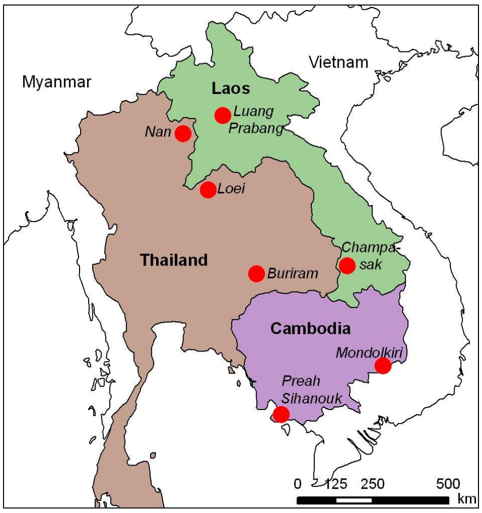

Figure 1: Locations of the seven study sites in Cambodia, Lao PDR and Thailand.

	Site	Date	Satellite / sensor
Cambodia	Mondolkiri	1988/02/12	SPOT1 / HRV1
		1998/03/28	SPOT1 / HRV2
		2008/03/16	SPOT5 / HRG1
	Preah Sihanouk	1992/06/08	SPOT2 / HRV1
		1997/12/29	SPOT1 / HRV1
		2006/12/19	SPOT5 / HRG1
		2007/03/22	SPOT5 / HRG1
Lao PDR	Luang Prabang	1987/02/27	SPOT1 / HRV1
		2006/10/31	SPOT5 / HRG2
		2007/01/03	SPOT5 / HRG1
	Champasak	1987/12/11	SPOT1 / HRV1
		1995/02/08	SPOT3 / HRV1
		2007/12/13	SPOT5 / HRG1
Thailand	Buriram	1991/01/20	SPOT2 / HRV2
		1998/01/26	SPOT 2 / HRV1
		2006/11/11	SPOT5 / HRG2
		2008/01/17	SPOT5 / HRG2
	Loei	1987/02/27	SPOT1 / HRV1
		1996/08/01	SPOT2 / HRV2
		2007/01/13	SPOT5 / HRG1
		2008/04/19	SPOT5 / HRG2
	Nan	1993/12/29	SPOT3 / HRV1
		1997/12/01	SPOT1 / HRV1
		2006/10/21	SPOT5 / HRG1
		2007/01/12	SPOT5 / HRG1

Table 2. Characteristics of SPOT scenes used in the study

2.2 Pre-processing

Pre-processing steps included accurate spatial registration, radiometric calibration and resampling of the multispectral images to the higher resolution of the panchromatic ones. Also texture indices (contrast and dissimilarity indices computed from the grey level co-occurrence matrix) (Haralick *et al.*, 1964) were derived from panchromatic images and slope was calculated from DEMs (ENVI® software).

2.3 Segmentation and classification of the most recent scene

For each site the most recent SPOT scene was segmented using the 'multiresolution segmentation' algorithm (eCognition Developer® software). The same segmentation parameters were used for all sites (Table 3). The delineated objects were then classified using a supervised process based on the objects intrinsic characteristics (reflectance values, shape and texture) including vegetation and water indices (McFeeters, 1996, Tucker, 1979, Xu, 2006). In a first level of segmentation, water bodies and built-up areas were extracted using boolean or fuzzy membership functions. Other objects were classified into different slope classes (Table 3). These latter were classified in a second level of segmentation into different wooded and agricultural classes (*e.g.* rice fields, rubber tree or teak plantations, secondary tropical rainforest) classes, based on a supervised nearest neighbour classifier requiring the selection of training samples (Table 3).

To allow inter-site comparison, objects were finally merged into four main classes: water, wooded areas, cultivated areas and built-up surfaces that are present in the seven study sites. Clouds and cloud shadows objects were masked.

Classification accuracy was assessed by field observations and photo interpretation using Google Earth®. 50 samples were randomly selected for each class and assigned to a class by a photo-interpreter who was not involved in the classification process. Using these ground-truth data, a confusion matrix was computed and two statistics were derived for each site, the overall accuracy and the Kappa index (Foody, 2002).

2.4 Changes detection

For each site, based on these four land-cover classes, new objects were delineated on older scenes using the same segmentation algorithm. These objects were classified in order to detect eventual land-cover change and if any, its nature (Table 3). The classification process, based on membership functions, used three types of object properties: intrinsic properties, topologic characteristics (relations to neighbouring objects) and contextual characteristics (semantic relationships between objects). The segmentation prior to object-based classification enabled to avoid obvious errors in classification and thus improve the post-classification comparison (Coppin *et al.*, 2001). Indeed, we considered in this procedure territory urbanization as a non-reversible process, following (Dupuy *et al.*, 2012): built-up surfaces in the most recent scenes can be classified as forested or cultivated areas in past images, but not the opposite.

		Segmentation				Classification	
	Segmentation level	**Spectral band[1] (weight)**	**Scale**	**Shape**	**Compactness**	**Type of classification**	**Object Features[2]**
Step 1: segmentation and classification of the most recent scene	Level 1	PAN (2) MS (1) PAN Haralick contrast (0) PAN Haralick Dissimilarity (0) Slope (0)	120	0.3	0.8	Fuzzy or Boolean membership functions	SWIR: Mean PAN: Haralick contrast, Haralick dissimilarity Brightness NDVI Slope: mean
	Level 2	PAN (2) MS (1) PAN Haralick contrast (0) PAN Haralick Dissimilarity (0) Slope (0)	200	0.1	0.5	Standard nearest neighbour classifier, using training samples	Green: mean Red: mean NIR: mean SWIR: mean PAN: mean, Haralick contrast, Haralick dissimilarity NDVI, NDWI, MNDWI Brightness
Step 2: Changes detection	Level 1	MS (0) Thematic: yes (classification Step 1)	200	0.9	0.5	Boolean membership functions	Thematic layer: classes of Step 1 classification
	Level 2	MS (1) Thematic: no	50	0.1	0.5	Fuzzy or Boolean membership functions	Red: mean of outer border NDVI Brightness Context: existence of super object

1: PAN: Panchromatic, MS: MultiSpectral
2: NIR: Near infrared, SWIR: Short-wavelength infrared, NDVI: Normalized Difference Vegetation Index (Tucker, 1979), NDWI: Normalized Difference Water Index (McFeeters, 1996), MNDWI: Modified Normalized Difference Water Index (Xu, 2006)

Table 3. Parameters used in the multi-resolution segmentation and image object classification

2.5 Object-based indices calculation

To allow comparison between sites, synthetic landscape indices were calculated from the classified objects using Fragstats software at the landscape level: proportion of each land-cover type, patch density, edge density, Shannon's Diversity Index (SHDI) and Simpson's Diversity Index (SIDI). These metrics were selected to reflect two main aspects of landscape ecology: area-density-edge aspects and diversity. Patch and edge densities indices can be interpreted as fragmentation indices whereas Shannon's and Simpson's Diversity indices rise with landscape heterogeneity (McGarigal *et al.*, 1995). Full detailed information on these metrics is available on the Fragstats site at www.umass.edu/landeco/research/fragstats/fragstats.html.
Annual land-cover changes rates were assessed for each site over the studied period.

3. RESULTS

Object-oriented classifications of the most recent scenes showed various forested ecosystems in the study sites (Figure 4). Among the different study sites, two sites (Luang Prabang, Lao PDR, and Mondolkiri, Cambodia) are largely covered by wooded areas (proportion of wooded areas > 50%). Most of the five other sites present similar proportions of forested and cultivated areas, except Buriram (Thailand), where agriculture takes over wooded areas (proportion of wooded areas < 30%). Moreover, large differences in the size of forested patches exist between the sites, with large wooded parcels in some locations (*e.g.* Mondolkiri) contrasting with smaller, fragmented wooded surfaces in other sites (*e.g.* Nan or Buriram, Thailand) (Figure 4).

Accuracy measures of the land cover maps showed a good agreement between the classification results and the ground-truth data, with fair to good overall accuracy rates, ranging from 0.64 (Buriram) to 0.82 (Mondolkiri) (Table 5). In Buriram, most errors occurred because isolated trees in cultivated parcels were classified as 'forest' whereas they were considered as 'cultures' by photo-interpretation.

Site	**Overall accuracy (%)**	**Kappa index**
Mondolkiri	82	0.76
Preah Sihanouk	74	0.69
Luang Prabang	73	0.67
Champasak	79	0.72
Buriram	64	0.47
Loei	68	0.62
Nan	81	0.74

Table 5. Accuracy measures of land cover classifications

Looking in the past, a diminution of forested areas was observed in all sites (example Figure 6). Deforestation rates ranged from 10.6% to 36.8% between the older and the most recent SPOT images, corresponding to annual deforestation rates of 0.65% (estimated in Buriram, Thailand) to 1.84% (Mondolkiri, Cambodia – see Figure 6).

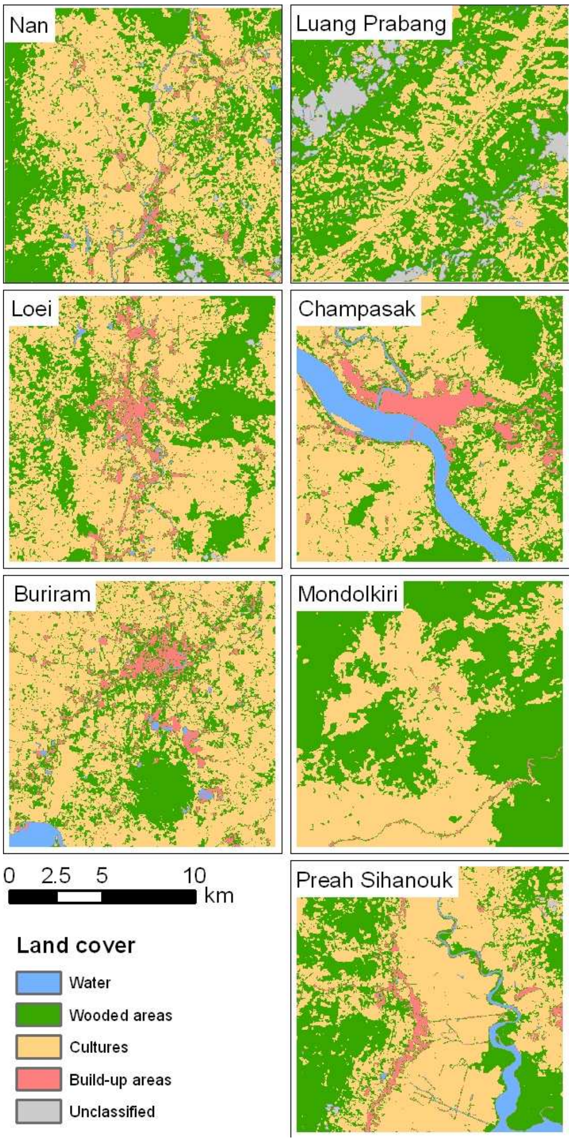

Figure 4: Land-cover maps of seven study sites in Southeast Asia, derived from SPOT imagery by object-oriented classification

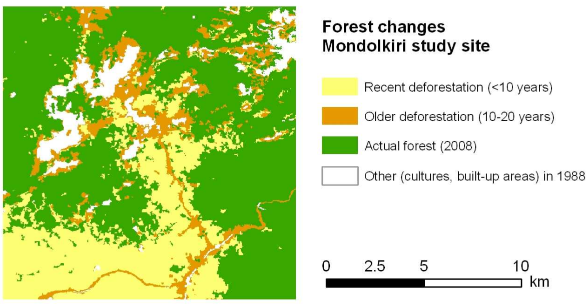

Figure 6: Forest changes classification, 1988-2008, Mondolkiri study site, Cambodia.

The analysis of the changes in the three main land cover types (built-up areas, agricultural areas and forested areas) showed a high variability of the land-cover dynamics between the different sites (Figure 7).

The conversion of forest to agricultural land seems to be the major cause of land cover changes in most of the sites, particularly in the sites with the highest deforestation rates (Mondolkiri and Preah Sihanouk in Cambodia and Luang Prabang in Lao PDR). Nevertheless, in other sites the proportion of cultivated areas remains stable (Buriram, Champasak): in that cases, land cover changes are mainly caused by the conversion of forest to built-up areas.

All landscape indices increase over the studied period in the seven study sites, reflecting an increase of both habitat fragmentation and landscape heterogeneity (Figure 8).
Though, large differences were observed on the landscape indices among the seven study sites. Overall, the three Thai sites (Buriram, Nan and Loei) have higher fragmentation indices (*e.g.* edge density index) than Lao sites (Champasak and Luang Prabang), which in turn have higher values of fragmentation indices than the Cambodian sites (Mondolkiri and Preah Sihanouk) (Figure 8a). Thus, the dynamics of habitat fragmentation appears to be different in the three countries. On the other hand, diversity indices values, which reflect the balance between the different land cover types, such as the SHDI, are higher when all land cover types are present in a site with similar proportions. From that point of view, the two sites with the larger woodland cover (Luang Prabang, Lao PDR, and Mondolkiri, Cambodia) have the lowest diversity indices, but with the highest increase over the last two decades (Figure 8b).

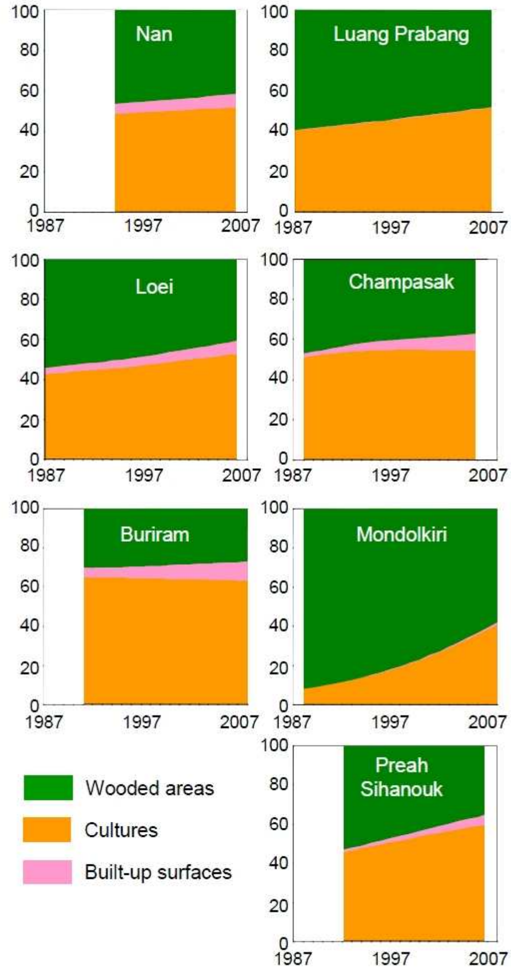

Figure 7: Evolution of the proportion of forested, cultivated and built-up areas within the seven study sites, 1987-2008.

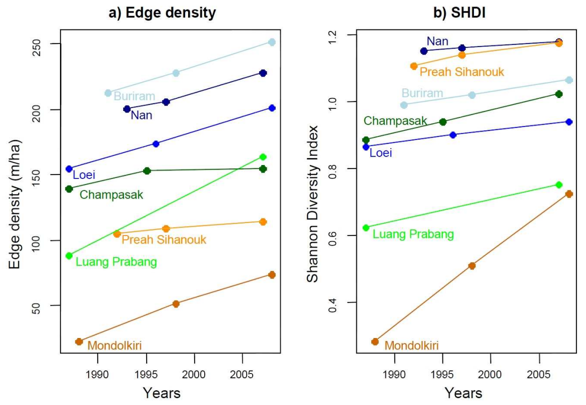

Figure 8: Evolution of landscape indices in seven study sites in Southeast Asia, 1987-2008. a) Edge density index b) Shannon's Diversity Index (SHDI). Index values of Thai, Lao and Cambodian study sites are plotted in blue, green and maroon colours, respectively.

4. DISCUSSION

Because of the high variety of landscapes among the seven study sites in Thailand, Lao PDR and Cambodia, we failed to implement a unique classification process for all sites: object features had to be fine-tuned to each site in a supervised classification process to discriminate between different agriculture and forest classes (Table 3). However, because SPOT images were acquired at the same spatial resolutions (2.5 m x 2.5 m for the most recent scene and 20 m x 20 m for older scenes), the same segmentation parameters were used for all study sites. Moreover, all sites could be processed identically for change detection, as membership functions were used. Overall, the method was efficient to process a high number of multispectral images (25), detect land cover changes and analyze them in terms of land cover dynamics, fragmentation and heterogeneity.

Our results illustrate the important land cover changes occurring in Southeast Asia over the two last decades and are consistent with annual deforestation rates estimated by programs such as the Global Forest Resources Assessment 2000 (FAO, 2001) or others research studies (Fox *et al.*, 2005, Giri *et al.*, 2003, Lambin *et al.*, 2003). Moreover, the use of an object based image analysis approach facilitated the calculation of landscape indices. Results of the spatio-temporal comparison of such indices put into evidence discrepancies in fragmentation indices between the three countries. Fragmentation indices being higher in Thailand than in Lao PDR and Cambodia suggest an older deforestation process in Thailand than in its neighbouring countries. The observation of the trends in land cover and landscape indices allow the identification of 'hot-spots' areas where land cover is changing at a quickening pace.

Nevertheless, all those changes may have various reasons (*e.g.* changes in demography or in agricultural practices, politics on forest conservation…) which may be site-specific and need further socio-economic investigation on land uses for a proper interpretation of the metrics derived from satellite imagery. In the future, the acquisition of images with a higher temporal resolution (*e.g.* every two years) will highly improve the detection and interpretation of land cover changes, in particular improving the detection of shifting cultivation parcels. Moreover, field-truth data are required to assess the accuracy of land cover maps produced at different dates. Such data are crucial in ecosystems experiencing important and rapid changes; they may be provided by land cover observatories or participative databases (Xiao *et al.*, 2011).

5. CONCLUSIONS

Object-oriented classification techniques applied on SPOT imagery were appropriate to map the land-cover on different study areas from Southeast Asia, allowing the analysis of land-cover changes over a twenty-year period.
Our study highlighted different spatio-temporal patterns of land-cover changes among the study sites. Perspectives of this work first concern the identification of the underlying driving factors (economic, institutional, technical, cultural, population) and secondly the study of the impact of those environmental changes on biodiversity changes, taking as example the rodent communities (Herbreteau *et al.*, 2006) and pathogens they carry (Ivanova *et al.*, in press).

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7. REFERENCES

Achard, F., *et al.*, 2002. Determination of deforestation rates of the world's humid tropical forests. *Science*, 297(5583), pp. 999-1002.

Chowdhury, R.R., 2006. Driving forces of tropical deforestation: The role of remote sensing and spatial models. *Singapore Journal of Tropical Geography*, 27(1), pp. 82-101.

Coppin, P., *et al.*, 2001. Digital change detection methods in natural ecosystem monitoring: a review. In: *Analysis of multi-temporal remote sensing images*, Singapore, Vol. 2, pp. 3-36.

Dupuy, S., *et al.*, 2012. An object-based image analysis method for monitoring land conversion by artificial sprawl use of RapidEye and IRS data. *Remote Sensing*, 4, pp. 404-423.

FAO, 2001. Global Forest Resources Assessment 2000. http://www.fao.org/docrep/004/y1997e/y1997e00.htm (accessed 20 February 2012)

Foody, G.M., 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80(1), pp. 185-201.

Fox, J. and Vogler, J.B., 2005. Land-use and land-cover change in montane mainland southeast Asia. *Environmental Management*, 36(3), pp. 394-403.

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), pp. 257-266.

Giri, C., *et al.*, 2003. Land cover characterization and mapping of continental Southeast Asia using multi-resolution satellite sensor data. *International Journal of Remote Sensing*, 24(21), pp. 4181-4196.

Haralick, R.M., *et al.*, 1964. Textural features for image classification. *IEEE Transactions on Systems, Man and Cybernetics*, 2, pp. 610-621.

Herbreteau, V., *et al.*, 2006. Perspectives on applied spatial analysis to animal health. *Impact of Emerging Zoonotic Diseases on Animal Health*, 1081, pp. 17-29.

Ivanova, S., *et al.*, in press. Leptospira and rodents in Cambodia: environmental determinants of infection. *American Journal of Tropical Medicine & Hygiene*.

Lambin, E.F., *et al.*, 2003. Dynamics of land-use and land-cover change in tropical regions. *Annual Review of Environment and Resources*, 28, pp. 205-241.

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), pp. 1425-1432.

McGarigal, K. and Marks, B.J., 1995. FRAGSTATS: Spatial Pattern Analysis Program for Quantifying Landscape Structure. http://www.fs.fed.us/pnw/publications/gtrs-prior-1997.shtml (accessed 20 February 2012)

Myers, N., *et al.*, 2000. Biodiversity hotspots for conservation priorities. *Nature*, 403(6772), pp. 853-858.

Sodhi, N.S., *et al.*, 2004. Southeast Asian biodiversity: an impending disaster. *Trends in Ecology & Evolution*, 19(12), pp. 654-660.

Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environments*, 8, pp. 127-150.

Xiao, X., *et al.*, 2011. A Library of Georeferenced Photos from the Field. *Eos, Transactions, American Geophysical Union*, 92(49), pp. 453-454.

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