Assessing the Immediate Impact of Surrounding Land Uses on the Extents of Freshwater Body over Time in Madagascar – A Demonstrative Case Study of Itasy Lake –

Masashi Konoshima^{1*}, Tetsuji Tonda², Ken-ichi Kamo³, Bam H. N. Razafindrabe¹

Abstract: Unplanned land use conversion driven by increasing food demand has threatened rich forest resources and freshwater fishery resources in Madagascar as a result of increasing sedimentation. For sustainable use of freshwater fishery resources, it is important to examine the impact of land use changes on sedimentation. Severe sedimentation often fills-in and shrinks lakes. Also, sedimentation causes lakebeds to rise, which can lead to flooding and therefore affect the position of the lake's boundary, over time. Recently available historical satellite images can be useful in assessing the changes in the position of lake boundaries over time. In this study, we propose a modeling approach for evaluating the impact of surrounding land uses on the extents of Lake Itasy, in Madagascar. In order to demonstrate our approach, we utilized satellite imagery available via Google earth to obtain a historical snapshot of the lake boundary. We delineated it and combined the results with a land use map. We then conducted a simple spatial statistics analysis using a logistic regression model with time varying coefficients. Our approach quantifies the impact of surrounding land uses on varying positions of lake boundaries over time.

Keywords: Madagascar, land uses, sedimentation, logistic regression, time varying coefficients

1. Introduction

Madagascar as a country is endowed with rich natural resources and is considered one of the top “hotspots” of biodiversity in the world (Myers et al. 2000). The landbase is forested with native vegetation covering around 9 to 11 million hectares (The World Bank 2013). The native vegetation is among the most biologically diverse rich species in the world (Ganzhorn et al. 2014). The vegetation is unique because between 80% and 90% of the plant and animal species can only be found in Madagascar (Phillipson et al. 2006). Although Madagascar occupies only about 0.4 percent of the world's landmass area, it has about 5 percent of the global biodiversity population (The World Bank 2013).

Madagascar is one of the poorest countries in the world (Minten et al. 2009; Rakotondramaro and Andriamasy 2016), with over 80% of the population living in poverty i.e., below US\$1.25 per day (Rakotondramaro and Andriamasy 2016). The GDP of Madagascar per capita in 2012 is US\$ 447 (Mohan and Shellard 2014), which is less than one tenth the GDP per capita of Japan in 2012.

In general, poor countries with rich natural resources tend to rely heavily and solely on these resources for subsistence and income (Miteva 2019). Natural resources are often the principal source of income or the mainstay of the economy in these countries (OECD 2008). This has led to heavy depletion of these resources (Das and Sarkar 2020) of which Madagascar is not an exception. Local communities in Madagascar rely on forests for fuel, shelter, medicine, and food production. Forestry resources are under pressure due to the high demand for agricultural and grazing land, illegal logging and timber export, and charcoal production and mining. Population pressure also exacerbates the situation as it brings about the clearing of forestlands for agriculture purpose (DeCosse 2001; Raik 2007; Freudenberg and Freudenberg 2002) which in turn threatens biodiversity in Madagascar's forests (The World Bank 2013).

Land conversion through slash-and-burn agriculture for rice cultivation (often called as “tavy”) has been one of the main causes of deforestation and land degradation (Styger et al. 2007; Klein 2002) in Madagascar, where rice is the staple food. Slash-and-burn agriculture accounts for 80 to 95 percent of deforestation (The World Bank, 2013). Itasy region, which is located in the central highlands of Madagascar, is one of the most important rice growing areas because of accessibility to the capital city of Antananarivo (Andriandralambo et al. 2017). Also, Lake itasy, is the third largest

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¹University of the Ryukyus, Japan

²Prefectural University of Hiroshima, Japan

³Sapporo Medical University, Japan

*Corresponding Author: konoshim@agr.u-ryukyu.ac.jp

lake in Madagascar and it is located in the middle of Itasy region. It serves as an important source of freshwater fisheries, which is the most popular animal protein for the Malagasy people. However, due to land conversion to rice farming, the wetland areas in the central highlands have been polluted with runoff from surrounding rice fields. Our semi-informal interview with local people (December, 2015) indicate that extinctions of freshwater fish have been occurring in this area. Around Lake Alaotra, the country's largest lake located in East-central highlands, the streams and rivers have been clogged due to deforestation of surrounding forests. Historical satellite images show that Lake Alaotra had shrunk to 20% of its former size by 2000 (Bakoariniaina *et al.* 2006).

The threat against sustainable use of fisheries resources posed by land conversion has been a growing concern for local communities in Itasy region. As a result, there is a pressing need for land use planners to consider the potential impact of land conversion on sedimentation. In order to develop an appropriate land use plan, it is necessary to evaluate the effect of surrounding land uses on sedimentation.

Severe sedimentation could result in diminishing lake size. Also, sedimentation causes lake bed to rise, which could result in flooding. Therefore, monitoring the extent of a lake boundary over time could provide useful information for assessing sedimentation. Although, field surveys have often been applied to monitor periodic changes in the positions of the lake's boundary (intersection between water surface and land) with high accuracy, these approaches are often labor-intensive, time-consuming and expensive (Liu *et al.* 2007; Natesan *et al.* 2013; Elnabwy *et al.* 2020). Recent studies show that sedimentation can be accessed by monitoring historical water boundary changes using Remote Sensing and Geographical Information Systems (GIS) techniques (Duru 2017). Acquiring data on spatial extent and temporal duration for evaluating changes on the shoreline of inland freshwater bodies and land use changes has become an easier task due to freely available remote sensing images. For example, Google Earth has provided historical satellite imagery in Google Earth's imagery archive which includes satellite imagery from various sources such as Landsat and MODIS (Woodcock *et al.* 2008). This kind of publicly available imagery archive allows us to develop land use maps in multiple time periods.

Over the past decade, a growing number of studies have used satellite imagery to assess land use changes and deforestation in Madagascar (Vågen 2006; Grinand *et al.* 2013; Elmqvist *et al.* 2007). In addition, a few studies have attempted to evaluate the impact of land use changes on sedimentation. Maina *et al.* (2013) used existing simulation models calibrated for Madagascar, to project the impact of land use changes on sediment yields in four watersheds, adjacent to major coral reefs. Their study showed that forest conversion increases sediment yield on those coral reefs. Although several studies have been conducted on soil erosion or sedimentation on Itasy lake, only a few of these studies have examined the effect of land uses on sedimentation or the extent of Itasy lake.

In this study, we utilize freely available satellite imagery via Google earth to propose a simple spatial logistic model with time varying coefficients to quantify the impact of immediate surrounding land uses on the extent of the lake over time. Our study demonstrates how a time varying coefficient model and publicly available historical satellite image data can be utilized in order to analyze the impact of land use change on the shoreline of inland freshwater bodies over time. The case study serves to illustrate the feasibility of our proposed modeling approach.

From statistical modeling perspective, despite the numerous application of time varying coefficient models (Tonda *et al.* 2011; Satoh *et al.* 2016; Alan *et al.* 2017) by Hastie and Tibshirani (1993), there is a limited application of this modeling approach to land use conversion risk. Although logistic regression models have been extensively used to predict the risk of the land use conversion for a particular parcel of land, these studies do not allow the regressors to be varied over time (Petit and Firbank 2006; Müller *et al.* 2011). However, the risk of land use conversion could be varied over time due to various factors. The approach utilized here allows us to quantify the longitudinal effect of independent variables (surrounding land uses) on the extents of the lake over time.

2. Methods

2.1. Study area

Our study area lies between the latitudes 19° 1'18" S to 19° 5' 55" S and longitudes 46° 44'1" E to 46° 49' 46" E and covers an area of about 3,500 ha (Figure 1). In this study, we extract the

area representing the intersection of the lake's water surface and its surrounding land in order to analyze the impact of the immediate surrounding of the land uses around the lake (Figure 2). Land uses of these intersection areas are classified into four different land uses, namely; water, rice field, agriculture crop production and grassland.

Figure 1. Location of the study area.

Figure 2. Intersection of the lake's water surface and its surrounding land (Shoreline).

2.2. Data

We downloaded 10 satellite images of 2003 (8/31), 2005(7/22, 10/15), 2009(9/22, 11/24), 2012(12/3), 2013 (5/11, 5/16, 7/15, 12/23) from Google earth for the demonstration of our proposed approach. We manually digitized the shoreline of the lake to monitor the changes in the lake's shoreline over time. We developed a grid-cell (raster) model, which is a relatively simple approach for representing spatial data. Each cell of the grid-cell model was coded according to the predominant land use in each cell. For illustration purpose we set the size of the grid as $200m \times 200m$. In order to estimate changes in shoreline of the lake, each image is classified into different land use classes, based on water or other land uses so that lake surface and surrounding ground can be precisely separated. All grid cells (a total of 560 cells) were used in developing the statistical model.

2.3. Model

We first begin with a conventional logistic model with coefficients which do not vary with time. Let p_i represent the probability of a grid cell i being part of the lake. The relationship between the land use types of eight adjacent grid cells of grid i and the probability of occurrence of lake in grid

cell i can be described using a multivariate logistic regression model (Kleinbaum and Klein 2010).

$$[1] \quad \log \frac{p_i}{1 - p_i} = \beta_0 + \beta_1 s_i + \beta_2 r_i + \beta_3 m_i$$

In order to consider a scenario where the probability can be varied over time, let $p_i(t)$ represent the probability of a grid cell i at time $t(=t_0, t_1, \dots, t_m)$ being the part of the lake. The relationship between the land use types of eight adjacent grid cells of grid i at time t_0 and the longitudinal change in the probability of the occurrence of a lake in grid cell i can be described using the following multivariate logistic regression model:

$$[2] \quad \log \frac{p_i(t)}{1 - p_i(t)} = \beta_0(t) + \beta_1(t) s_i + \beta_2(t) r_i + \beta_3(t) m_i$$

where s_i represents a dummy variable which takes on a value of 1 if adjacent grid cells contain a grassland, and 0 if otherwise. Similarly, r_i represents a dummy variable which takes on a value of 1 if adjacent grid cells contain rice field, and 0 if otherwise. Finally, m_i represents a dummy variable which takes on a value of 1 if adjacent grid cells contain agricultural crop production, and 0 if otherwise. $\beta_j(t)$ are time varying coefficients (Hastie and Tibshirani 1993) which represent the impacts of adjacent land uses. Assume the following functional form for $\beta_j(t)$

$$[3] \quad \beta_j(t) = \theta'_j \mathbf{x}(t)$$

where $\mathbf{x}(t)$ is a vector of a basis function used to describe the shape of $\beta_j(t)$. For example, $\mathbf{x}(t)=(1, t)'$ if we assume a linear trend on impact of adjacent land use. Then, unknown parameters θ_j can be estimated as interactions between bases $\mathbf{x}(t)$ and covariates, s_i, r_i, m_i through maximum likelihood estimation (Satoh et al. 2009). Our proposed model is built upon the study by Satoh et al. (2009) who developed a methodology for estimating time varying coefficients based on conventional multivariate analysis procedures by expressing time varying coefficients in the form of $\theta'_j \mathbf{x}(t)$. By introducing $\beta_j(t)$ in a logistic regression model, this model allows us to estimate longitudinal effects of adjacent land uses. The methodologically interested reader is referred to Satoh et al. (2009) for more detail understanding. In order to explore the best model for the shape of $\beta_j(t)$, we perform variable selection based on AIC (Akaike 1973). Statistical analysis was conducted using R software (R Development Core Team 2011).

3. Results

Figure 3 shows the changing positions of the lake's shoreline (changes in the intersection of a lake's water surface and its surrounding land). As depicted in Table 1, dominant land uses at the intersection of a lake's water surface and its surrounding land has been water (47 - 51%) and rice field (26 - 28%).

Table 2 summarizes the results from assuming a linear function for the functional form of $\beta_j(t)$ in the model [1]. Table 3 summarizes the results of the optimal model using minimize AIC to select the structure of $\beta_j(t)$. The hyphen sign “-” represents the variables removed based on AIC model selection. As Table 3 shows, the probability that adjacent grids of the lake were classified as “water” in 2003(August) is 88% ($p < 0.001$). No change in the land use classes was detected ($p = 0.672$). The probability that the adjacent grids of agriculture crop production or grassland were classified as “water” in 2003 (August) is significantly lower (the odds ratio for agriculture crop production and grassland were $\exp(-2.097) \approx 0.123$, and $\exp(-1.860) \approx 0.156$, respectively) compared with the case where the adjacent grids of the lake. And “time constant” models were selected for the structure for these time varying coefficients. The probability that the adjacent grids of rice fields was classified as “water” in 2003 (August) is significantly lower (the odds ratio was $\exp(-1.487) \approx 0.226$) compared with the case where the adjacent grids are the lake. The model capturing the increasing risk of converting to the lake over time was selected (the odds ratio was $\exp(0.028) \approx 1.028$).

Figure 4 shows the longitudinal change of the risk that the grid adjacent to the rice field changes to lake, and the dotted line is the 95% simultaneous confidence interval. Odds ratio show that the risk of conversion to a lake increases over time if the surrounding areas are rice fields.

Table 1. Changes in the number of grids of each land use.

	2003 08 – 31	2005 07 – 22	2005 10 – 15	2009 09 – 22	2009 11 – 24	2012 12 – 03	2013 05 – 11	2013 05 – 16	2013 07 – 15	2013 12 – 23
Rice field	154	153	156	148	143	146	152	153	159	151
Agriculture	62	67	61	52	56	57	54	57	53	50
Grassland	80	78	78	75	76	75	76	76	72	77
Water	264	262	265	285	285	282	278	274	276	282

Table 2. Parameters estimation based on linear $\beta_j(t)$.

		Estimate	S.E	p value
Water $\beta_0(t)$	Intercept	2.057	0.138	< 0.001
	Slope	0.001	0.018	0.971
Agriculture $\beta_1(t)$	Intercept	-2.096	0.145	< 0.001
	Slope	0.000	0.019	0.998
Rice field $\beta_2(t)$	Intercept	-1.488	0.144	< 0.001
	Slope	0.028	0.019	0.138
Grassland $\beta_3(t)$	Intercept	-1.934	0.147	< 0.001
	Slope	0.011	0.019	0.569

Table 3. Parameters estimation based on AIC model selection for $\beta_j(t)$ structure.

		Estimate	S.E	p value
Water $\beta_0(t)$	Intercept	2.039	0.086	< 0.001
	Slope	0.003	0.008	0.672
Agriculture $\beta_1(t)$	Intercept	-2.097	0.071	< 0.001
	Slope	–	–	–
Rice field $\beta_2(t)$	Intercept	-1.487	0.126	< 0.001
	Slope	0.028	0.016	0.077
Grassland $\beta_3(t)$	Intercept	-1.860	0.072	< 0.001
	Slope	–	–	–

Figure 3. Changes in the intersection of a lake's water surface and its surrounding land over time.

Figure 4. Longitudinal effect of adjacent rice field on the risk of being converted to lake.

4. Discussion and Conclusions

Inland fishery based on lacustrine fisheries is important resources in Madagascar where people rely on fish for animal protein (Breuil and Grima 2014). However, sedimentation caused by deforestation and agriculture development in the basin areas has led to serious environmental problems in freshwater bodies in Madagascar (Breuil and Grima 2014). One of the most concerned land conversions is slash and burn agriculture for rice cultivation which has been triggered by the increasing demand for rice, the main staple food for the people of Madagascar, due to rapid population growth (annual population growth of 2.9% between 2005 to 2010 as reported by the United Nations (UNFPA 2012) in Madagascar. Expansion of rice fields to meet increasing demand undermines fishery production which is an important source of animal protein. Although, it has been a while since rice-fish farming system (which is growing fish and rice simultaneously), was introduced in Madagascar. This system has not been implemented extensively (Halwart 1998) and is far from being an effective tool for addressing this issue. It is important to develop land use plan considering the effect of land use on sedimentation in freshwater bodies in Madagascar.

Detecting and monitoring the changes in shoreline of the lake (changes in the intersection of a lake's water surface and its surrounding land) are essential for sustainable lake resource management because sedimentation often affect the surface area of lake. The extent of soil erosion and sedimentation in the area may increase as Itasy region is considered to be among the areas with the highest rate of deforestation in the previous decades (IMF 2009). Agricultural practices located on steep slopes, as well as frequent wild fires occurring in the region are the main causes of soil erosion and sedimentation bordering the lake (MAEP 2006). Integrating this temporal information with land use map, allows us to analyze the impact of land use on the extents of the lake. In this study, we utilized historical satellite images of the lake boundary and combined that with land use map in order to evaluate the impact of land uses on the extent of the lake, in Madagascar.

We develop a simple logistic model with time varying coefficients for land conversion in Itasy region, which includes Madagascar's third largest lake, Lake Itasy. It is one of the most productive rice growing areas. This study is among the pioneers in attempting to quantify the impact of immediate surrounding of land uses on the extents of the lake in Itasy region, over time. Our approach is constrained by the limitations of currently available satellite imagery provided via Google earth. For simple demonstration purpose of our approach, we used the data from Google earth without accessing the original data source information (such as the type of sensor used, atmospheric correction, cloud score etc.,) because Google earth provides already processed images for easy

visualization (Magaña et al. 2014; Kumar and Mutanga 2018). Future studies should carefully consider accessing the original data source of images used so that numerical results obtained could be more meaningful, than just an illustration of the modeling approach. In addition, we relied on a manual digitizing method to detect the shoreline. Although by combining this approach with ground surveys, we can further improve the quality of shoreline position detection (Li et al. 2002). These approaches are time consuming and labor intensive. Various classification techniques have been proposed to automatically detect water and non-water objects (Dewi et al. 2016). For example, Dewi et al. (2016) developed a fuzzy classification method for detecting changes in shoreline by explicitly considering a transition zone between water and non-water objects, and their imprecise boundaries. Future studies can utilize these techniques to improve the quality of a database and the efficiency of database development process so that more satellite images from other sources other than a free application can be included for the analysis.

Also, for illustration purpose, we set various assumptions to simplify the problem. For example, we conducted a statistical analysis based only on a grid size of 200 m. In future studies, we can develop land use data at various resolutions and explore the effects of grid size on our statistical analysis, which will allow us to find the reasonable grid size for the analysis (Bormann 2006).

Our results did not show any significant longitudinal effects of adjacent land uses. Considering only adjacent land uses may not be enough to successfully capture factors that affect changes in the shoreline (position of water boundaries) of the lake. In this study, we focused on land uses adjacent to the lake. These immediate surrounding areas of the lake contain similar topographic conditions because all sites are on gentle slope directed downward towards the lake. However, in order to identify longitudinal effects of land uses on the extent of water boundaries, it will be important to expand the area over immediate surrounding of the lake so that we can evaluate the impact of spatial patterns of the land uses as well as topographic conditions of sedimentation on the lake. Also, future studies should consider seasonal effects such as rain events.

Due to these limitations and simplifications in our modeling approach, the results must be thoroughly verified before it is used for any land management plans. Rather our results should be taken as an indication of the need for further analysis with additional supplementary data.

Despite these limitations, our study demonstrates how publicly available satellite image archive can be used to develop a data set required for statistical analysis, and shows how a time varying coefficient model can be used to quantify the impact of immediate surrounding land uses on the extents of the lake over time. Through our personal communication with local people (December 2015), we found that local people have been feeling the threat against sustainable use of fishery resources that pose periodic changes to water boundaries. Assessing the impact of surrounding land uses on the extent of water boundaries is the first step toward developing effective measure against serious sedimentation. This study shows that our approach can quantify the effect of surrounding land uses on the extent of water boundaries and can be a useful approach in the development of land use plans. Finally, this study provides an avenue for future researchers to conduct a quick assessment of the effect of surrounding land uses on the extent of a lake, with relatively low cost modeling process. Our approach neither requires expensive software for the analysis nor high-cost satellite imagery to develop a database. In addition to freely available satellite images, R software, which was used to develop the logistic model with time varying coefficients, is also freely available from public domain. Hence, our approach is easily replicable in other financially-challenged regions where sufficient data are not readily available.

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