Satellite-Based Modeling of *Anopheles* Mosquito Densities on Heterogeneous Land Cover in Western Thailand

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Abstract
Landsat 5 TM was used as a tool to model *Anopheles* mosquito densities on heterogeneous land cover. In this study, mosquito density data was divided into five classes; absence, low, moderate, high, and very high densities. Land cover was classified into eight types. Stagnant water, wetland, and paddy land cover types are larva habitat. Forest, cropland, orchard, and grassland land cover types are adult habitat. Built-up land is non habitat. Multiple linear regression and discriminant analysis were selected to identify the relationship between mosquito densities and land cover types. For the average flight range of mosquitoes, 1000, 2000, and 3000 meters buffer were used as the sample zones around the collected points to test the relationship between them. The results revealed that discriminant analysis is the best statistical model for fitting the model. The mosquito flight range of 1000, 2000, and 3000 meters were predicted with accuracies up to 80%, followed by 74.3%, and 54.3%, respectively. Relationships between mosquito density and heterogeneous land cover in this study appear to be varied upon forest, grassland, and larva habitat within the 1000 meters buffer, likewise, forest, and larva habitat within 2000 meters buffer.
Keywords
Anopheles mosquito densities, Landsat5 TM, land cover classification, mosquito life cycle, statistical model

I. INTRODUCTION

Malaria is one of the high priority tropical diseases in Thailand. Although, there have been many efforts to eradicate malaria from the world over a long period of time, yet it remains a complex disease. It affects human health and continues to be one of the most serious vector-borne diseases world-wide. Malaria transmits through three possible mediums; malaria parasite, human hosts, and *Anopheles* mosquito. The way to solve the malaria problem is to intervene these mediums. This study focused on *Anopheles* mosquito, a part of the malaria transmission cycle. The suitable environmental conditions for various behaviors of *Anopheles* mosquito such as resting, swarming, oviposition, biting, and feeding are examined. The characteristic of heterogeneous space is an important factor to predict the mosquito densities. The heterogeneous space is called "land cover".

Heterogeneous land cover encourages vector-borne disease transmission in several ways. Recent studies found that mosquito density correlated with forest mean patch size and fruit orchard fractal dimension (Overgaad, et al., 2001). Furthermore, the landscape features correlated with the density of *An. Albimanus* and malaria incidence (Beck et al., 1994; Rejmankova et al., 1995; Snow et al., 1998). Some studies show the relationship between land use and mosquito density, for instance dam creation and urbanization have increased mosquito productivity (Patz, et al., 2000; Norris, 2004).

Malaria has been studied using remotely sensed data. NOAA and METEOSAT, weather monitoring satellite, are the most effective in predicting changes in malaria transmission dynamics. Thomson et al. (1997) found the positive relationship between rainfall and NDVI value and vector abundance. Nualchawee et al. (1997) and Montgometry et al. (1998) used Landsat to study the relationship between the incidence of malaria transmission and vegetation covers. Some studies show that land cover classes affect malaria transmission. Moreover, satellite imagery was applied to extract the parameters and found the association with the mosquitoes. Also, Barnes and Cibula (1979), Later Hayes et al. (1985) and Thomas and Lindsay (2000) used Landsat 1, 2 and SPOT to classify vegetation cover, fresh water plants, and land cover types. The result revealed that these parameters associated with the breeding habitat. Land cover and NDVI values are significantly correlated with density of mosquitoes (Pope, et al., 1994; Thomson, et al., 1997). The immature collections of *Anopheles* mosquitoes are significantly correlated with land use as determined in the land use classification (Sithiprasasna, et al., 2005). Mosquito larva habitats are associated with wetland areas and aquatic vegetation (Kaya, et al., 2004;Vasconcelos, Novo, 2003). Cross et al. (1984) used Landsat MSS data to describe the geographic (landscape) characteristics of sites in the Philippine Islands where cases of schistosoiasis were reported. These measurements were combined with temperature and precipitation data to estimate the probability of disease occurrence at specific locations. Beside, NOAA AVHRR data is used to infer ecological parameters associated with Rift Valley Fever (RVF) in Kenya. Correlations between vegetation index values and ecological parameters indicated the possibility of predicting RVF viral activity in the mosquito vector (Linthicum, et al., 1987). This work was extended by Pope et al. (1992) who used Landsat TM to identify potential vector breeding sites known as *dambos*.

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In other words, mathematical models provide a sound understanding risks and planning for control in heterogeneous environments, especially when the models are based on the ecology of the local vector populations and a sound understanding of the entomological parameters relevant for transmission (Killeen, et al., 2000). They can bridge the gaps between landscape ecology, vector biology, and human epidemiology, linking large-scale maps to individual risk in local human populations at spatial scales ranging from 10 meters up to 10 kilometers (Bidlingmyer, 1985).

Fewer studies have examined the prediction mosquito density on heterogeneous land cover. The focus of this study was therefore to create model for predicting *Anopheles* mosquito densities which based on satellite imagery into classify heterogeneous land cover. Remote sensing technology was used to answer the questions by linking between the *Anopheles* mosquito densities, mosquito habitat, mosquito life cycle, and heterogeneous land cover. A spatial density pattern of mosquito was determined, then analyzed to obtain the correlation with land cover types. Also, the relationship between land cover and habitats of *Anopheles* mosquito was determined. The best fitted model was derived from statistical models. Knowledge of the effects of land cover types and topography on mosquito habitat distribution is useful for predicting the density of *Anopheles* mosquito and the impacts of different land cover types practice on malaria transmission, and thus for designing novel strategies for malaria intervention.

II. STUDYAREA

The number of malaria reported cases in Thailand show a decreasing trend during past two decades, and even disappearing from most of the major cities (Ministry of Public Health, 2003). However, people in rural areas, especially in villages along the Thailand-Myanmar and Thailand-Cambodia borders and forested mountain areas, remain at great risk (Somboon, et al., 1998). In these endemic areas, malaria transmission has been considered to have a close association with the forest and movement of the human population (Ministry of Public Health, 2003). However, little is known about spatial patterns and dynamics of malaria in Thailand.

This study was conducted in some areas of Sai Yok district in the western part of Kanchanaburi province, Thailand (latitude 14°15' N and longitude 99°20' E) (Figure 1).

III. METHODOLOGY

Workflow of the study is shown in Figure 2. Landsat 5 TM image (Figure 2) was classified into different land cover types. Mosquito density data was divided into five classes, and each class had three buffer zones. GIS technique was used to overlay their outputs. Two statistical models were applied to model the relationship between mosquito densities and land

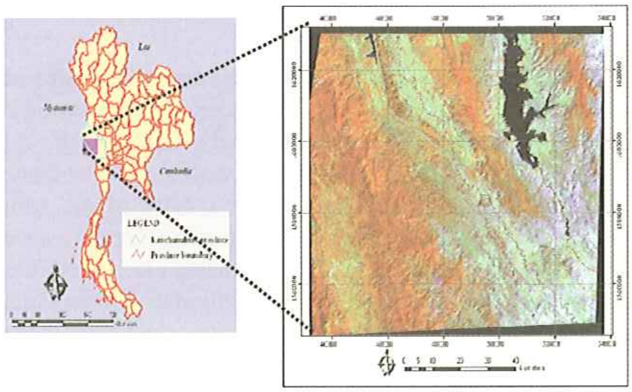


Figure 1. Study area in some areas of Sai Yok district, Kanchanaburi province, Thailand

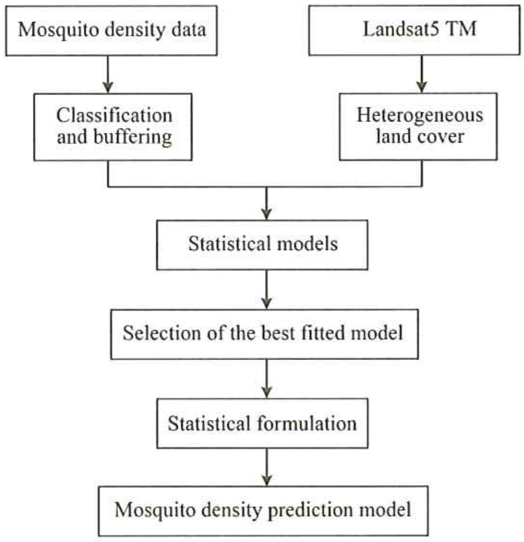


Figure 2. Workflow of the study

cover types, with the used of average flight range of the mosquitoes. Mosquito density prediction model is the final output of this study.

A. Mosquito data

Mosquito data was obtained from Vector Borne Disease Control Center 4.1 Kanchanaburi. There are four species of *Anopheles* mosquitoes found in Sai Yok district, the study area. They are as follows:

- Primary vector
  —*Anopheles* minimus
  —*An.* dirus
  —*An.* maculatus
- Secondary vector
  —*An.* aconitus

Although, these species have their feeding behaviors both outdoor and indoor environment, this study however only focused on outdoor behavior, as it would not be possible to apply satellite imagery to extract the parameters for indoor. Four

Anopheles mosquito species were grouped together in the map.

While larva and pupa densities do not necessarily correlate with adult emergence success, they are commonly used as a surrogate for adult productivity in surveillance and control surveys, and ecological studies (WHO, 1982). Hence, this study used only the density of adult mosquito. The density of the adult mosquitoes was collected in the malaria transmission area, about thirty one sub-villages and in the free malaria area about four sub-villages. Sampling was performed through outdoor biting and resting collections. The collection was carried-out in wet season (July-August). Average density of *Anopheles* mosquito was estimated by the averaging number of female mosquito bits per collector per hour. The mosquito densities were divided into five classes; they are absence, low density, moderate density, high density, and very high density, depending up on with the ranges of 0, 1—5, 6—11, 12—19, and 20—45 females bite/person/hour, respectively (Table 1).

B. Buffering

A buffer is a polygon that encloses all areas within a set distance of the spatial features. In this study, buffer zones were created around every point that represents adult mosquito sources in the mosquito density map. These buffer zones were divided into three groups according to the average distance that *Anopheles* mosquito would travel per day. Therefore, the buffer zones of 1000 meters, 2000 meters, and 3000 meters around every *Anopheles* mosquito collected points (mosquito density) were created by using GIS.

Table 1. *Anopheles* mosquito density classes in the study area

Sub-village	Tambon	Category	Mosquito density
Wang Sing	Sing	Absence	0
Nong Pralai	Sing	Absence	0
Yang Ton	Sri Mongkol	Absence	0
Nong Prue	Sing	Absence	0
Lawa Cave	Wang Krajae	Low	0.56
Pak Lum	Wang Krajae	Low	0.67
Pu Namron	Lum Sum	Low	1
Mu Supan	Lum Sum	Low	2
Nong Hoi	Sri Mongkol	Low	2.12
Samukkee Thum	Lum Sum	Low	2.43
Kata Thong	Sri Mongkol	Low	3
Huai Kawlam	Bong Ty	Low	3.09
Kaeng Pralom	Sai Yok	Low	3.33
Mae Nam Noi	Sai Yok	Low	5
Pu Rungroeng	Sri Mongkol	Moderate	5.33
Hat Ngiu	Wang Krajae	Moderate	5.66
Huai Manow	Bong Ty	Moderate	6
Dong Pong	Wang Krajae	Moderate	6
Rai Zak	Wang Krajae	Moderate	6.78
Nong Pladook	Sri Mongkol	Moderate	7.32
Ton Mamuang	Wang Krajae	Moderate	9.08
Thung Ma Soe Yo	Bong Ty	Moderate	9.43
Chy Thung	Wang Krajae	Moderate	9.59
Sri Mongkol	Sri Mongkol	Moderate	11
Bong Ty Noi	Wang Krajae	Moderate	11
Khao Yai	Bong Ty	Moderate	11.32
Hin Kong	Bong Ty	High	12
Phu Toei	Bong Ty	High	12
Prado Thong	Bong Ty	High	12.2
Ton Tal	Bong Ty	High	13
Kho Kae	Wang Krajae	High	15
Bong Ty Bon	Bong Ty	Very high	35
Pang Mai	Bong Ty	Very high	35
Bong Ty Lang	Bong Ty	Very high	42.12
Thai Mueang	Bong Ty	Very high	45.29

C. Satellite imagery

The land cover types were classified by using Landsat5 TM. TM is one of the most applicable satellites for environmental studies. TM has seven bands; six of them are in the visible and near infrared wavelength and one of them is in the thermal infrared wavelength. Satellite imagery was required to cover the Sai Yok district, with path: 130 and row: 50, in wet season (August) in 2005.

D. Land cover classification

Supervised classification method was used to classify the land cover types. This was done by defining regions of interests (ROIs) that represent each of the land cover types. Utmost attention was made in selecting ROIs that are homogeneous by exporting them to n-D Visualizer function of ENVI 4.X image processing software and correcting for overlaps between classes. After the ROIs are finalized, maximum likelihood classification was performed to assign each pixel in the subset image data to the class that has the highest probability.

There are eight land cover types in this study area. They are stagnant water, wetland, paddy, forest, orchard, cropland, grassland, and built-up land. Each type relates to the mosquito life cycle. Creating of the mosquito density map requires mapping of larva and adult habitat. These maps were combined with a real mosquito density from filed surveying. Eggs, larva, and pupa habitat are called larva habitat. These were extracted from only stagnant/standing water such as reservoir, pond, well, wetland and paddy. While the adult habitat appears in four land cover types; forest, grassland, orchard, and cropland. The built-up land was defined as mosquito non-habitation area (Figure 3).

E. Statistical models

Two statistical models, multiple linear regression and discriminant analysis, were applied to create the model. Multiple linear regression was applied to create the model to illustrate relationship between *Anopheles* mosquito density zones (1000 meters, 2000 meters, and 3000 meters buffer) and land cover types. The multiple regression equation takes the form as follows;

$$y = b_1x_1 + b_2x_2 + \ldots + b_nx_n + c$$

where the b's are regression coefficients, the x's are the score of the variables or predictors and c is a constant.

Discriminant analysis, stepwise method, was also applied to

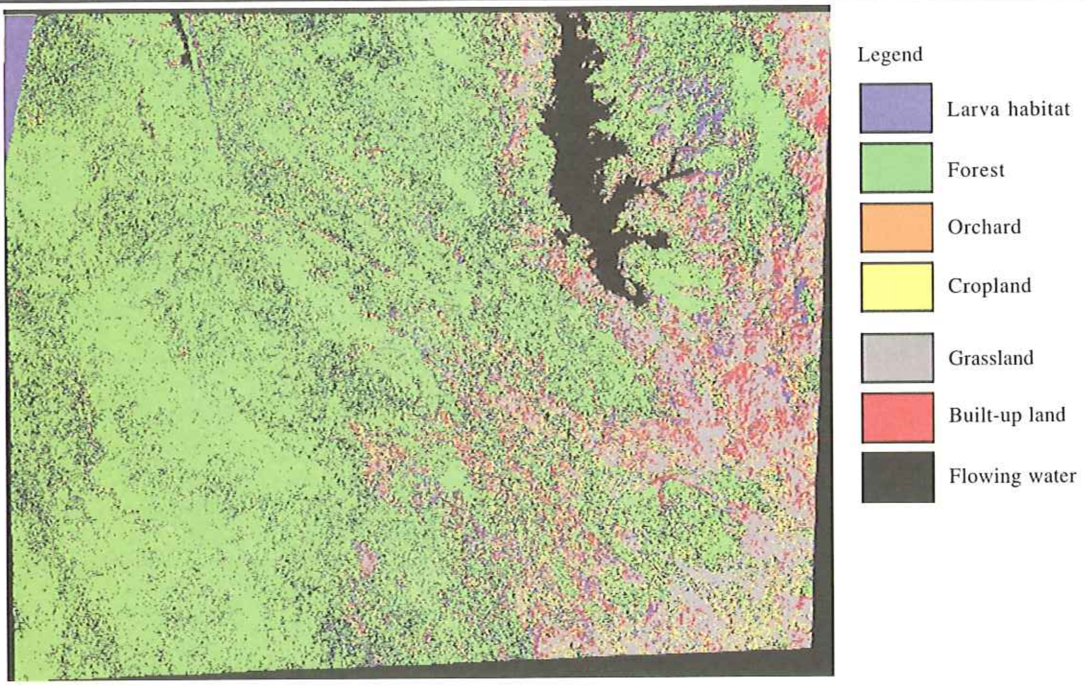


Figure 3. Land cover types in the study area

create the model. The model is built based on a set of observations for which the classes are known. This set of observations is sometimes referred to as the training set. Based on the training set, the technique constructs a set of linear functions of the predictors, known as discriminant functions, such that

$$L = b_1x_1 + b_2x_2 + \ldots + b_nx_n + c$$

where the b's are discriminant coefficients, the x's are the input variables or predictors and c is a constant. It was used to determine which variables discriminant between five naturally occurring groups.

IV. RESULTS AND DISCUSSION

Three models were created as shown in Table 2 and Table 3. However, the models that were able to predict the mosquito density correctly more than 70% are model 1 (=1000 meters) and model 2 (=2000 meters), with the accuracy 80% and 74.3%, respectively. In comparison, model 3 (=3000 meters) was able to predict correctly only 54.3%. Independent variables of the model 1 were forest1000, grassland1000, and larva habitat1000 land cover types within 1000 meters buffer to predict mosquito density. For model 2, then, forest2000 and larva habitat2000 were identified as the independent variables within 2000 meters buffer to predict mosquito density (see also in Figure 4).

For model 1:

Absence = –13.582+3.202(forest1000)+5.502(grassland1000)+ 3.944(larva habitat1000) (1)

Low =–34.836–9.893(forest1000)+12.726 (grassland1000)+ 6.779(larva habitat1000) (2)

Moderate = –36.973+0.802(forest1000)+ 13.07 (grassland1000)+5.829 (larva habitat1000) (3)

High = –53.738+28.729(forest1000)+10.167 (grassland1000)+ 5.273(larva habitat1000) (4)

Very high = –71.217+45.237(forest1000)+8.992 (grassland1000)+ 4.13(larva habitat1000) (5)

The results of each density class for model 1 was able to identify correctly 100% of the absence, 80% of the low, 66.7% of the moderate, 100% of the high, and 75% of the very high density (Table 3).

For model 2:

Absence = –13.198+22.507(forest2000)+ 31.167 (larva habitat2000) (6)

Low = –14.749+10.710(forest2000)+41.74(larva habitat2000) (7)

Moderate = –26.642+19.488(forest2000)+ 55.538 (larva habitat2000) (8)

High = –40.12+29.306(forest2000)+66.006(larva habitat2000) (9)

Very high = –64.455+48.97(forest2000)+ 75.757 (larva habitat2000) (10)

Otherwise, the results of each density class for model 2 was able to identify correctly 75% of the absence, 80% of the low, 75% of the moderate, 60% of the high, and 75% of the very high density.

Each class of the mosquito density of the two models could determine some optimal combinations of variable, in which the function 1 provides the most overall discrimination

Table 2. Results from the discriminant analysis model

Independent Variable	Mosquito density classes (Dependent Variable)				
	Absence	Low	Moderate	High	Very high
Model 1(=1000 meters)					
Forest1000	3.202	−9.893	0.802	28.729	45.237
Grassland1000	5.502	12.726	13.07	10.167	8.992
Larva habitat1000	3.944	6.779	5.829	5.273	4.13
Constant	−13.582	−34.836	−36.973	−53.738	−71.217
Function1 at group centriods	−1.974	−2.708	−0.562	3.426	6.146
Function2 at group centriods	−3.252	0.438	0.836	−0.034	−0.309
Model 2(=2000 meters)					
Forest2000	22.507	10.71	19.488	29.306	48.97
Larva habitat2000	31.167	41.74	55.538	66.006	75.757
Constant	−13.198	−14.749	−26.642	−40.12	−64.455
Function1 at group centriods	−1.777	−2.014	−0.003	1.826	4.538
Function2 at group centriods	1.755	−0.197	−0.478	−0.396	0.667
Model 3(=3000 meters)					
Forest3000	4.538	6.754	7.413	9.12	10.576
Constant	−10.539	−21.391	−25.435	−37.669	−50.105

Table 3. Classification results

	Density class	Predicted group membership									
		Absence		Low		Moderate		High		Very high	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Cross-Validated(%)	Absence	**100**	**75**	.0	25	.0	.0	.0	.0	.0	.0
	Low	10	.0	**80**	**80**	10	20	.0	.0	.0	.0
	Moderate	.0	.0	25	8.3	**66.7**	**75**	8.4	16.7	.0	.0
	High	.0	.0	.0	.0	.0	20	**100**	**60**	.0	20
	Very high	.0	.0	.0	.0	.0	.0	25	25	**75**	**75**

Model 1=80% of cross-validated grouped cases correctly classified.
Model 2=74.3% of cross-validated grouped cases correctly classified

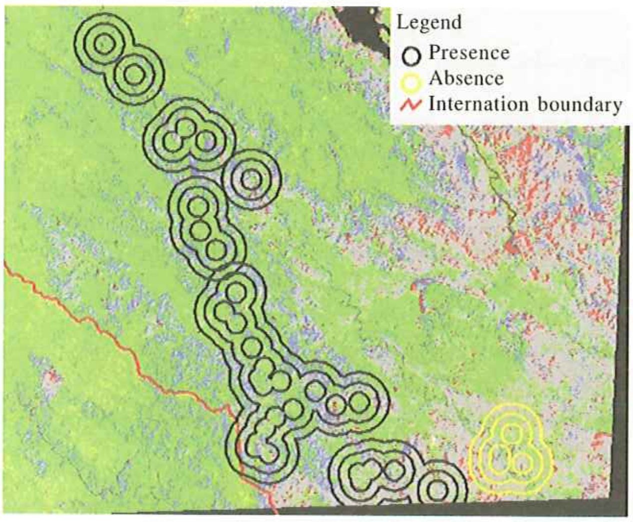
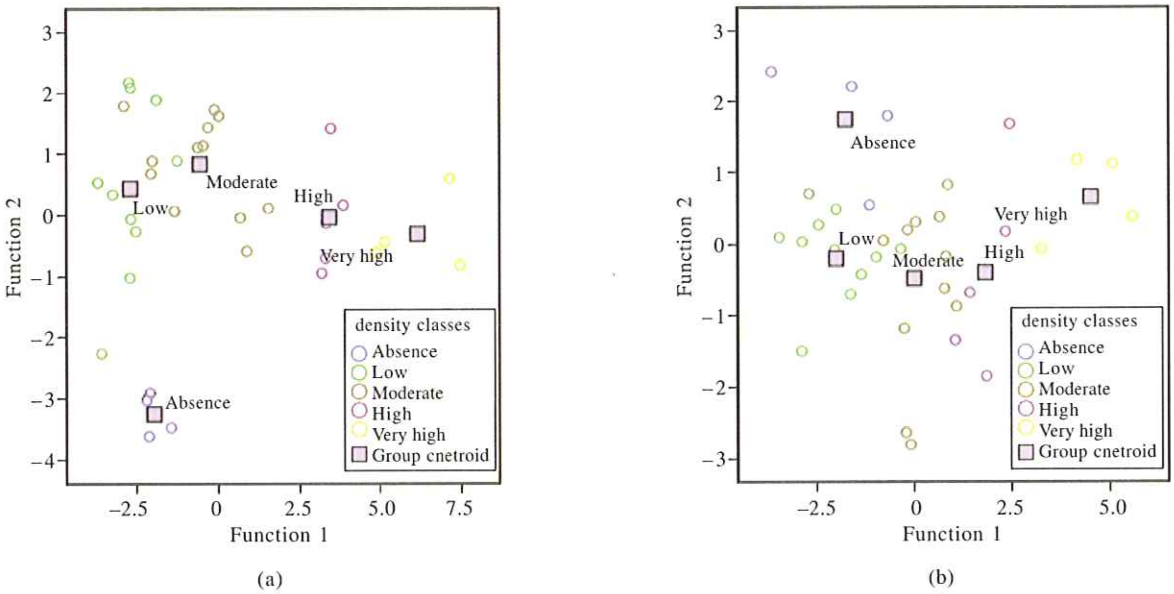


Figure 4. Buffer zones of 1000, 2000, and 3000 meters related to land cover types

between groups, followed by function 2 (see also Figure 5). Moreover, the functions that are independent would have their contributions to the discrimination between groups not overlapped. For model 1, function 1 seems to discriminant mostly between groups moderate (–0.562), high (3.426), and very high (6.146) combined. In the vertical direction, absence (–3.252), low (0.438), and moderate (0.836) were discriminant mostly between groups. Then, function 1 of model 2 showed that discriminant mostly between groups moderate (–0.003), high (1.826), and very high (4.538) combined. In the vertical direction, absence (1.755), low (–0.197), and very high (0.667) were discriminant mostly between groups. Whereas, the model 3 identified correctly less than 70% so that it did not display canonical discriminant function.

V. DISCUSSION AND CONCLUSION

This study addresses spatial patterns of *Anopheles* mosquito



(a) (b)

Figure 5. Canonical discriminant functions of model 1(=1000meters) (a) and model 2(=2000meters) (b)

densities through the use of remotely sensed data. It focused on the relationship of mosquito life cycle, heterogeneous land cover and mosquito densities and habitats, to create the mosquito density prediction model. The model accuracy of mosquito densities was negatively correlated with buffer zone distance from *Anopheles* mosquito collected points. The result commonly confirms that the closer distance to the mosquito collected points, the better prediction accuracy of the mosquito density it gets. The previous studies found that the mosquito average flight range is approximately 1000—3000 meters, depending on the environmental condition and time, such as wind direction, wind current, physical barrier, hill, tree, distance from breeding source and human habitat, etc.

The result shows that each type of land covers influence differently to the mosquito density. This also supports to the previous finding that land use influences the density of immature mosquitoes in larva habitat (Gratz, 1999; Patz, et al., 2000). This study reveals a significant relationship between heterogeneous land cover and mosquito densities. Among 1000 meters, 2000 meters, and 3000 meters buffer, the forest land cover type has the highest correlation with mosquito densities, followed by grassland land cover type and larva habitat land cover types (stagnant water, wetland, and paddy). In other word, forest would have more distribution and density of mosquito. The previous work, similarly, has shown that *Anopheles* mosquito correlated positive with forest mean patch size (Overgaard, et al., 2001).

Discriminant analysis is found to be the best statistical model for fitting the models to predict the *Anopheles* mosquito densities on heterogeneous land cover. The model was able to correctly identified 80% and 74.3% of five density classes of 1000 meters and 2000 meters buffer, respectively. Similar method was used by Beck et al. (1994) could identify high risk, low risk and non-malarious villages with 90% accuracy buffer of 1 kilometer around villages. Condition Autoregressive (CAR) model is the best fitted model for mosquito density prediction in the indoor environment. Then, a climate-based statistical model of transmission intensity was developed (Snow, et al., 1998). This model correctly identified 75% of three endemic classes. The model was applied to meteorological and remotely sensed data using GIS to provide estimates of endemic. Rainfall and temperature data were derived from weather station reports, whereas NDVI was extracted from NOAA-AVHRR satellite sensor. These data were resampled according to the location of the parasitological surveys (Smith, et al., 1995).

The result of discriminant analysis is the model to predict mosquito density. In Table 3, the model shows that the Absence and High density classes in Model 1 have the accuracy of 100%, the highest among the other. The Low density class in both Model 1 and Model 2 has the accuracy of 80%. Absence density class in Model 2 and Very high density class in Model 1 and Model 2 have the accuracy of 75%. The results of this study are similar with other previous studies. Those studies used three ranges of average travel distance, they are 0–500, 501–1500 and >1500 meters. The adult mosquito density in houses that are near to the larva habitats were recorded as landing rate of 0.5 mosquitoes per human per minute. Predictions of mosquito densities have an accuracy up to 89% for high density sites, while 100% for the sites more than 1500 meters away, was low (Rejmankova, et al., 1995). In another study, a step-wise discriminant analysis, using Landsat TM channels, was performed to predict high and low mosquito-producing fields. The results of the analysis were correctly identified of 75% of the high, and 80% of the low producing fields (Wood, et al., 1992).

The result of this study is a useful tool to help in forecasting of malaria transmission by knowing where land cover types would appear the malaria vector or where the suitable habitats of malaria vector would be. The result could also be applied to vector control measure by environmental management method for man-mosquito contact reduction. This measure was proved from many countries that can reduce the vector density and breeding sources.

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REFERENCES

[1] Barnes C., Cibula W., 1979, Some implications of remote sensing technology in insect control programs including mosquitoes. Mosq. News, 39: 271—282.

[2] Beck L R., Rodríguez M H., Dister S W., Rodríguez A D., Rejmankova E., Ulloa A., Meza R A., Roberts D R., Paris J F., Spanner M A., Washino R K., Hacker C., and Legters L J., 1994, Remote sensing as a landscape epidemiological tool to identify villages at high risk for malaria transmission. Am. J. Trop. Med. Hyg, 51(3): 271—280.

[3] Bian L., Li L., Yan G., 2006, Combining global and local estimates for spatial distribution of mosquito larval habitats. GIScience and Remote Sensing, 43(1): 95—108.

[4] Bidlingmyer W L., 1985, The measurement of adult mosquito population change-Some considerations. J. Am. Mosq. Control Assoc, 1: 328—348.

[5] Calcerrada R., Luque S., 2006, Habitat quality assessment using Weights-of-Evidence based GIS modelling: The case of Picoides tridactylus as species indicator of the biodiversity value of the Finnish forest. Ecological Modelling, In Press.

[6] Gratz N G., 1999, Emerging and resurging vector-borne diseases. Annual Review of Entomology, 44: 51—75.

[7] Jeffrey S., Marc S., Mark C., Marc S., 2006, A hydrologically driven model of swamp water mosquito population dynamics. Ecological modeling, 194: 395—404.

[8] Kaya S., Sokol J., Pultz T J., 2004, Monitoring environmental indicators of vector-borne disease from space: a new opportunity for RADARSAT-2. Can. J. Remote Sensing, 30(3): 560—565.

[9] Killeen G F., McKenzie F E., Foy B D., Schieffelin C., Billingsley P F., Beier J C., 2000a, A simplified model for predicting malaria entomologic inoculation rates based on entomologic and parasitologic patterns relevant to control. Am. J. Trop. Med. Hyg, 62 (5): 535—544.

[10] Killeen G F., McKenzie F E., Foy B D., Schieffelin C., Billingsley P F., Beier J C., 2000b, The potential impact of integrated malaria transmission control on entomologic inoculation rate in highly endemic areas. Am. J. Trop. Med. Hyg., 62 (5): 545—551.

[11] Mushinzimanal E., Mungal S., Minakawa N., Li L., Feng C., Bian L., Kitron U., Schmidt C., Beck L., Zhou G., Githeko A K., Yan G., 2006, Landscape determinants and remote sensing of anopheline mosquito larval habitats in the western Kenya highlands. Malaria Journal, 5(13): 1—11.

[12] Norris D E., 2004, Mosquito-borne diseases as a consequence of land use change. Ecohealth, 1: 19—24; DOI: 10.1007/s10393-004-0008-7.

[13] Omumbo J A., Hay S I., Snow R W., Tatem A J., Ragers D J., 2005, Modelling malaria risk in East Africa at high-spatial resolution. Tropical Medicine and International Health, 10(6): 557—566.

[14] Overgaard H J., Ekbom B., Suwonkerd W., Takagi M., 2003, Effect of landscape structure on anopheline mosquito density and diversity in northern Thailand: Implications for malaria transmission and control. Landscape Ecology, 18: 605—619.

[15] Patz J A., Graczyk T K., Geller N., Vittor A Y., 2000, Effects of environmental change on emerging parasitic disease. International Journal for Parasitology, 30: 1395—1405.

[16] Pope K O., Rejmankova E., Savage H M., Arredondo-Jimenez J T., Rodriguez M H., Robert D R., 1994, Remote sensing of tropical wetlands for malaria control in Chiapas, Mexico. Ecological Application, 4(1): 81—90.

[17] Rejmankova E., Roberts D R., Pawley A., Manguin S., Polanco J., 1995, Predictions of adult *Anopheles albimanus* densities in villages based on distance to remotely sensed larval habitats. Am. J. Trop. Med. Hyg., 53: 428—488.

[18] Robert S U., Tonya S., Charles R K., Eddie W C., Geoffrey E H., Thomas R U., 2006, A dynamic transmission model of eastern equine encephalitis virus. Ecological Modelling, 192: 425—440.

[19] Sithiprasasna R., Lee W J., Ugsang D M., Linthicum K J., 2005, Identification and characterization of larval and adult anopheline mosquito habitats in the Pepublic of Korea: potential use of remotely sensed data to estimate mosquito distributions. International Journal of Health Geographics, 4: 17—27.

[20] Smith T., Charlwood J D., Takken W., Tanner M., Spiegelhalter D J., 1995, Mapping the densities of malaria vectors within a single village. Acta Tropica, 59: 1—18.

[21] Snow R W., Gouws E., Omumbo J., Rapuoda B., Craig M H., Tanser F C., Sueur D., Ouma J., 1998, Models to predict the intensity of Plasmodium falciparum transmission: applications to the burden of disease in Kenya. Tropical Medicine and Hygiene, 92: 601—606.

[22] Somboon P., Aramrattana A., Lines J., Webber R., 1998, Entomological and epidemiological investigations of malaria transmission in relation to population movement in forest areas of north-west Thailand. Southeast Asia J. Trop. Med. Public Health, 29: 3—9.

[23] Surya K S., Prajesh K T., Khageswar P., Ashok K U., Mohammed A H., Nutan N., Hema J., Sukla B., Tridibes A., Bhawani S D., Virander S C., Chetan E C., Sarala K S., 2006, Epidemiology of malaria transmission in forest and plain ecotype villages in Sundargarh District, Orissa, India. Tropical Medicine and Hygiene, 100: 917—925.

[24] Thomas C J., Lindsay S W., 2000, Local-scale variation in malaria infection amongst rural Gambian children estimated by satellite remote sensing. Tropical Medicine and Hygiene, 94: 159—163.

[25] Thomson M C., Connor S J., Milligan P., Flasse S P., 1997, Mapping Malaria Risk in Africa: What can Satellite Data Contribute? Parasitology Today, 13(8): 313—318.

[26] WHO, 1982, Mosquito, mosquito-borne disease and mosquito control methods: a review. In: Manual on Environmental Management for mosquito Control with Special Emphasis on Malaria Vectors, Geneva: World Health Organization, 11—22.

[27] Wood B L., Beck L R., Washino R K., Hibbard K A., Salute J S., 1992, Estimating high mosquito producing rice fields using spectral and spatial data. Int. J. Remote Sensing, 13(15): 2813—2826.