Predicting Asian Elephant Habitat Suitability with Satellite Data and GIS

MONGKOLSAWAT C. and CHANKET U.
Geo-informatics Centre for Development of Northeast Thailand
Faculty of Science, Khon Kaen University
Khon Kaen Province, 40002, Thailand.
Email: charat@kku.ac.th, eurawa@kku.ac.th

KEY WORDS: Asian elephant Habitat, GIS, GPS, Satellite image

ABSTRACT:
The encroachment of agriculture on forest reserves in Thailand has brought about a decreasing wildlife population. Identification of potential habitat sites is a prerequisite for subsequent protection. This study is aimed at predicting the habitat suitability for Asian elephant in Phu Luang Wildlife Sanctuary, Northeast Thailand. The habitat suitability study involved an analysis of the complex interrelationship among various environments and life requisites for the elephants over a geographical area. We investigated the areas along the line intersection made across diversity of the forest and identified the wildlife tracks. The conditions preferred by the Asian elephants were recorded in relation to locations. In addition, the information derived from the Landsat TM, topographic map and GPS were compiled to create the thematic layers. The thematic layers include food and cover (vegetation type, water resource, cropping plot and salt lick), physical landscape and distance to human activity sites. Matrix overlay on the layers was digitally performed to generate habitat suitability map for the Asian elephant. Field check, based on the map output and frequency of the elephant tracks, was conducted to validate the resulting map. A predictive spatial model of the Asian elephant habitat was developed in order to identify potential areas requiring preservation. The habitat suitability for Asian elephants in the Phu Luang Wildlife Sanctuary covers an area of 19.15%, 35.03% and 45.83% for high, moderate and marginally suitable respectively.

1. Background

As forest resources in Thailand are being destroyed and converted to agricultural uses, native wildlife habitats are inevitably threatened to ensure the long-term persistence of the forest crisis and conserve the resources. As a result of the forest clearing, it has had effects not only on surface water hydrology but also has threatened the wildlife habitat as well. To organize plan and project in accordance with the forest land management, a number of wildlife sanctuaries were established. Phu Luang Wildlife Sanctuary (PLWS) was established in 1974 with objectives of preventing and conserving wildlife habitat under strictly legal measures. The previous study conducted by Wildlife Division and Khon Kaen University (2002) revealed that the PLWS has a number of endangered species including birds and wild mammals. Asian elephant is among the wild mammals inhabiting in the PLWS and is being pushed to extinction. The Asian elephant need a lot of space and a lot of food. As a result it requires the study of habitat suitability for the Asian elephants in the PLWS. With an advent of spatial technologies, they can be used to predict and model the habitat suitability. Spatial technologies should be considered as tools to assist resource manages with mapping and as a way to merge data sets from a variety of sources into one format (O’Neil et al., 2005). Zhixi et al., (1995) provided an approach to quantitatively analyze the habitat suitability for the Asian elephant based on the linear combination of variables and field
investigation. Bristow et al. (2005) developed logistic regression models to predict habitat use of scaled quail. In addition, the models calculated a modified Akaike’s Selection Criterion to select the most parsimonious model. Rushton et al. (2004) reviewed methodologies and approaches used in modeling species distribution in articles published in the Journal of Applied Ecology since 2000. They provided a number of models using logistic regression with and without GIS application.

The objective of this study is to predict the habitat suitability for the Asian elephant in the PLWS, Northeast Thailand with the integration of the variables using GIS.

2. Description of the study area

The study area, the PLWS, is located in Loei Province, Northeast Thailand (Fig.1) and covers an area of about 900 km² with elevation differences between 400 m. on the foot hills and 1,600 m. on its summit. It is characterized by a number of hills with a thick sequence of Mesozoic rocks of Phu Khadung, Soa Khua, Pha Dua, Phu Phan and Phra Wihan geological Formations. The mean annual rainfall of the area varied from 1,200-1,400 mm.; with over 60% of the annual rain falls in August and September. The areas support three main forest types: hill evergreen forest, dry evergreen forest and dry dipterocarp forest. The total depletion of forest area by type since the establishment of the PLWS (1974) to date is approximately 17.07%, 51.62%, and 55.94% for hill evergreen forest, dry evergreen forest and dry dipterocarp forests respectively. (Mongkolsawat et al.,2005) The PLWS was rich with forest resource and numerous wildlife species. There exists a number of endangered species of birds and wild mammals (Wildlife Division and Khon Kaen University, 2000)

3. Method

3.1 Analysis of habitat variables

This study implements a synergistic approach, combining ground survey and spatial analysis of habitat variables. Based on habitat variables for Asian Elephant documented in the scientific literature and ground survey, we established the ranges of conditions preferred by Asian elephant. The ground surveys were conducted during the dry season (November-February). Tracks selected by line transect through different ecosystem were transverse slowly on foot. The location of Asian elephant tracks either footprint and/or dung observed was recorded using a global positioning system (GPS) with an accuracy of ± 10 m. In addition the investigation of the ranges of conditions preferred by Asian elephant was recorded in relation to the numbers of tracks. The habitat variables include forest type, water resource, salt lick, elevation, slope, surface material, community, cropping plot, protection unit of the sanctuary and road.
3.2 Model for the habitat suitability

The logistic regression model offers the methods for predicting where wildlife should occur. The model, in particular, links the incidence of species to habitat variables and has increasingly formed the backbone of the modeling approaches used (Ruston et al., 2004) Remote sensing and GIS have further broadened these modeling application. Due to forest complexity in the tropical region, there exists no adequate information in determining the coefficients for the logistic regression model requires efforts to establish the coefficients in the model. In addition an intensive field survey is needed to identify the variables preferred by the wildlife and to determine the number of wildlife per unit area. As a result in the PLWS we then established the habitat for Asian elephant, based on the condition preferred by Asian elephant and variable combination with the matrix overlay. This is the first approximation for the further model development. The variables consist of an integration of food and cover, physical landscape and human activities. Each of which is a thematic data layers resulting of sub-layers concerned. The thematic data layers are then integrated to ultimately form a composites output later or habitat suitability for Asian elephant.

3.3 Establishment of GIS layers

The habitat suitability for Asian Elephant was based on a combination of variables: Food and cover, physical landscape and human activities. Each of which is a thematic data layers that is a result of an analysis of sub layer or individual layer.

The GIS layers in the PLWS was derived from the following sources.
1) Landsat TM acquired on February 25, 2005 which corresponded to the dry season
2) Topographic maps of The Royal Thai Survey Department at the scale 1:50,000 which were used for geo-referencing and supplement information.

Figure 2: Schematic chart of analyzing habitat suitability for Asian Elephant
Table 1: Variables and GIS layers used to predict potential Asian Elephant habitat.

<table>
<thead>
<tr>
<th>Variable/GIS layers</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food and cover</td>
<td>Landsat TM, Topographic map</td>
</tr>
<tr>
<td>Vegetation type</td>
<td>Ground survey/GPS</td>
</tr>
<tr>
<td>Water resource</td>
<td>DEM, Topographic map</td>
</tr>
<tr>
<td>Cropping plot</td>
<td>Landsat TM, Topographic map</td>
</tr>
<tr>
<td>Salt lick</td>
<td>Ground survey/GPS</td>
</tr>
<tr>
<td>Physical landscape</td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td></td>
</tr>
<tr>
<td>Human activity</td>
<td></td>
</tr>
<tr>
<td>Community</td>
<td></td>
</tr>
<tr>
<td>Road</td>
<td></td>
</tr>
<tr>
<td>Protection unit</td>
<td></td>
</tr>
</tbody>
</table>

The processing of image includes geometric correction, enhancement and classification. The digital images were registered to the topographic maps (1:50,000) and applied the nearest neighbor interpolation for re-sampling of pixel values. The data was then linearly enhanced to produce images for further analysis. The RGB (453) color composite images were generated and used for further analysis. A land cover map was produced on which we can establish GIS layers and its associated attributes of vegetation type, water resource, community, cropping plot and road. In addition, distance to certain variables was digitally performed. GPS survey offered locations of salt lick and the protection unit on which the GIS layers of their buffering zones could be established. DEM generated from the elevation contour lines was used to produce elevation and slope polygons. The variables, GIS layers and sources of information used to predict potential Asian elephant habitat were presented in table 1.

The process of analyzing the habitat suitability for Asian elephant is shown in figure 2.

3.4 Habitat suitability

Input data layers for the food and cover include vegetation type, water resource, cropping plot and salt licks.

The physical landscape layer is a combination of slope and elevation of the area.

The human activity in the PLWS is a combination of the community, the protection unit and roads on which we established the areas beyond these locations.

The variables and their associated attributes were given and the analysis and procedure were executed, based on the matrix overlay with suitability class for each sub layers (table 2).

The resulting thematic layer represents the integration of the food and cover, physical landscape and the human activities which are assigned the habitat suitability accordingly.

Table 2: Result of the variables and their associated attributes

<table>
<thead>
<tr>
<th>Variables</th>
<th>Attribute</th>
<th>suitability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation type</td>
<td>Hill Evergreen forest</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Dry Evergreen forest</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Grassland</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Agriculture</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Pine forest</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Deciduous forest</td>
<td>1</td>
</tr>
<tr>
<td>Distance to Water resource (m.)</td>
<td>&lt;1,200</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>1,200-2,250</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>&gt;2,250</td>
<td>1</td>
</tr>
<tr>
<td>Distance to Salt-lick (m.)</td>
<td>&lt;1,400</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>1,400-3,000</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>&gt;3,000</td>
<td>1</td>
</tr>
<tr>
<td>Distance to Cropping plot (m.)</td>
<td>&lt;1,200</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>1,200-2,700</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>&gt;2,700</td>
<td>1</td>
</tr>
<tr>
<td>Elevation (m.)</td>
<td>500-1,300</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>400-500</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>&lt;400 or &gt;1,300</td>
<td>1</td>
</tr>
<tr>
<td>Slope (%)</td>
<td>0-2</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2-10</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>&gt;10</td>
<td>1</td>
</tr>
<tr>
<td>Distance to Village (m.)</td>
<td>&gt;5000</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>3,800-5,000</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>&lt;3,800</td>
<td>1</td>
</tr>
<tr>
<td>Distance to Protection unit (m.)</td>
<td>1,000-2,700</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>&gt;2,700</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>&lt;1,000</td>
<td>1</td>
</tr>
<tr>
<td>Distance to road (m.)</td>
<td>2,300-4,000</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>1,000-2,500</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>&lt;1,000</td>
<td>1</td>
</tr>
</tbody>
</table>

3 = Highly, 2 = Moderately, 1 = Marginally
4. Results and Discussion

To select range of habitat variables we used the field survey and references that presented data most appreciate to the establishment of GIS layers. The area with Asian elephant habitat in the PLWS encompassed 19.15%, 35.03% and 45.83% for highly suitable, moderately suitable and marginally suitable respectively. The highly suitable habitat distributes over the areas where there exist, the most preference of the GIS layers identified. These areas are evergreen forests, that having water resource, salt lick, favorable physical landscape and far from the community. Their distribution is limited by both the need for access to water and availability of food. Asian elephant eats around 300 kg. of fodder per day. As a result incident of elephants raiding the cropping plots are on the rise. The habitat suitability map for Asian elephant resulting from the spatial overlay of thematic layers in the PLWS is presented in fig. 3 the corresponding area for Asian elephant is shown in Table 3.

This study method identifies the current ability of the area to provide Asian elephant with environmental conditions preferred for food, cover and space. This would reflect existing vegetation cover of the PLWS as influenced by natural and man caused disturbance.

To validate the study result we overlay the elephant tracks on the suitability map. The abundance of the tracks was found in the highly suitable area as seen in Figure 4.

We are able to develop a GIS-based map of potential Asian elephant habitat in the PLWS that correctly predicted over 75% of elephants found during the ground survey. However it would suggest caution in the application of this model. Numerous factors likely contribute to the apparent inaccuracies of the output map. The validation method was less than perfect because the presence of elephant in some areas unlikely fitted to the condition defined.

<table>
<thead>
<tr>
<th>Suitability</th>
<th>Areas (Km²)</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highly Suitable</td>
<td>174.26</td>
<td>19.15</td>
</tr>
<tr>
<td>Moderate Suitable</td>
<td>318.85</td>
<td>35.03</td>
</tr>
<tr>
<td>Marginally Suitable</td>
<td>417.10</td>
<td>45.83</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>910.21</strong></td>
<td><strong>100.00</strong></td>
</tr>
</tbody>
</table>

Figure 3: Habitat suitability for Asian elephant in the PWLS

Figure 4: The number of elephant tracks and the habitat suitability.
In conclusion for Asian elephant it is possible to evaluate the habitat with identification of food and cover, physical landscape and human activities. A long term study may need to predict the habitat suitability for Asian Elephant with detailed ground survey. The result provides the first approximation for further study and logistic regression model is recommended. The geoinformatics technologies offer the tool to effectively model the habitat suitability with its capability in the variable integration. Estimation of actual population in the suitability zone is beyond the scope of this study. The computer-base of GIS provides information rapidly available for up-dated model in case of future knowledge enhanced.

5. References


EVALUATING LAND SUITABILITY FOR INDUSTRIAL SUGARCANE WITH GIS MODELING.

PAIBOONSAK S. and MONGKOLSAWAT C.
Geo-informatics Centre for Development of Northeast Thailand
Computer Center Building. Khon Kaen University
Khon Kaen Province, 40002, Thailand.
Email: sathaprn@kku.ac.th
Tel: (+66) 43-348268 Fax: (+66) 43-348267

KEY WORDS: Land Suitability, Land Evaluation, Sugarcane, Geographic Information System

ABSTRACT: In Thailand sugarcane is considered as one of the most important crops. The importance of sugarcane is more than a subsistence crop. Thailand has developed a large and complex industrial system for processing and marketing of crop. To increase the productivity of sugarcane, the cultivation should be based on the suitability of land. The study was then aimed at identifying the land with suitability for sugarcane. The crop is cultivated mainly in the Northeastern part of Thailand where there are 15 sugar factories. The study area is then focused in this region. The evaluation is based on the method as described by FAO and used GIS capability for an integration of land qualities to create land unit. The crop requirement was studied from the previous experiments, literature reviews and ground investigation. Matching the land unit to the sugarcane requirement could be performed. The land qualities include water availability, soil, and topography. Each of the land qualities was digitally encoded in GIS database and subsequently performed the overlay process. The model criteria were organized and iterated to achieve a reliable results. The result obtained reveals that the area is approximately 10.94, 20.20, 12.43, 43.00, 11.68 and 1.74% of the total Northeast for highly suitable, moderately suitable, marginally suitable, unsuitable, unclassified area and water body respectively. This study provides an approach to identify parametric rating of the land qualities and overall insight into the integration of land qualities in relation to the suitability of land.

1. BACKGROUND

Thai sugarcane production represents 3.8 percent of world sugarcane production in 2000 and Thailand ranked fifth among world producers (Office of Agricultural Economic, 2007). The Northeastern region has the planted area of sugarcane, representing 34.5 percent of the national total or 323,925 ha in 2006. The average sugarcane yield in the North-East was estimated to be 47 ton/ha. All sugarcane produced in the North-East are supplied to sugar factories. There are 15 sugar factories in the North-East, distributing in 9 provinces. Sugarcane is usually planted either before or after the rainy season and can be harvested around 10 to 12 months after cultivation. A large number of farmers grow sugarcane on the basis of marketing price rather than the highly potential soils. Lands inherently unsuitable and depleted are used to plant sugarcane, resulting low productivity. As a consequence, the farmers suffered from increasing debt. The allocation of sugarcane to suitable land is needed to enhance the productivity. The land suitability, based on integration of land qualities is widely accepted. FAO guideline on the land evaluation (1983) is well known worldwide for land suitability evaluation method. In addition a number of reports provide methodologies on the application of GIS to the land evaluation (Mongkolsawat et al, 1999;
Charuppat, 2002; Thavone, 1999; Paiboonsak et al, 2004; Maleki et al, 2006) The land evaluation for sugar-cane was conducted with objective of identify spatial information of land suitability based on an integration of land qualities as related to sugar-cane requirement.

2. THE STUDY AREA

The study area, Northeastern Thailand, covers an area of 170,000 sq km with elevation differences between 120-1700 m, 1700 m on the North-western portion and 120 m on the low land of the South-eastern portion (Fig 1). Physiographically, the North-East is formed by the strong topography in the North-western portion and flat to gently undulating landscapes in the central portion. The land cover encompasses of dipterocarp and evergreen forests in the upland mountain zone, field crops on the well drained soil of the gently undulating areas and paddy rice on the flat and low lying areas. The soils on the undulating landscapes are mainly derived from alluvium of sandstone origin. The mean annual rainfall ranges from 1000-2500 mm and increases from the Southwest to the Northeast portions of the region.

3. METHODOLOGY

3.1 Analysis of Land Suitability

The process of evaluating the land in the Northeast is based on the FAO guidelines for land evaluation (FAO, 1983). This study implemented a synergistic approach, creating land unit as a result of land quality combination related to crop requirement. The land qualities or thematic layers were digitally encoded in GIS database and eventually performed the overlay of the thematic layers. With defined model for the sugarcane the output layer was classified into 4 classes: highly suitable(S1), moderately suitable(S2), marginally suitable(S3) and not suitable(N).

3.2 Crop Requirement

The sugar-cane requirements in terms of the land qualities to be used in the evaluation process were reviewed (Sys et al, 1993; FAO, 1983; Mongkolsawat et al, 1999; Charuppat, 2002; Thavone, 1999; Paiboonsak et al, 2004; Maleki et al, 2006). Furthermore a number of field experiments and regional experiences were also reviewed to support define the land qualities. In the North-East, the qualities used in this evaluation were selected with reference to the sugarcane land use and the nature of land unit. The land qualities used in this evaluation included water availability (W), nutrient availability index (NAI), particle size (PS), rooting conditions (R) and topography (TOPO). Each was considered as a thematic layer in the GIS database. Determinations of the diagnostic factors and the factor ratings are summarized in table 1.

3.3 GIS Layer Establishment

a) Water Availability (W)

Rainfall data of 30 years (1976-2005) recorded by the Metheorological Department was used for the establishment of the "W". Spatial interpolation of mean annual rainfall for the entire
North-East Thailand was undertaken with kriging method of the rainfall data to yield "W" spatial map. The spatial "W" layer was then divided into 4 classes.

**Table 1** Land use requirement for sugarcane

<table>
<thead>
<tr>
<th>Land Quality</th>
<th>Land use requirement</th>
<th>Diagnostic Factor</th>
<th>Unit</th>
<th>Factor Rating</th>
<th>N(0.1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nutrient Availability (W)</td>
<td>Annual Rainfall</td>
<td>N x P x K x pH</td>
<td>mm.</td>
<td>S1(1.0)</td>
<td>S2(0.8)</td>
</tr>
<tr>
<td>Water Availability (W)</td>
<td>&gt;1600</td>
<td>1,100-1,600</td>
<td>800-1,100</td>
<td>&lt;800</td>
<td></td>
</tr>
<tr>
<td>Nutrient Available Index (NAI)</td>
<td>6-25</td>
<td>30-60</td>
<td>7.9-8.4</td>
<td>&gt;8.4</td>
<td></td>
</tr>
<tr>
<td>Soil Quality Diagnostic Factor</td>
<td>0.1-0.2</td>
<td>&lt;0.1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>%</td>
<td>&gt;0.2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P ppm</td>
<td>&gt;25</td>
<td>6-25</td>
<td>&lt;6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>K ppm</td>
<td>&gt;60</td>
<td>7.4-7.8</td>
<td>&lt;6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>pH</td>
<td>6.1-7.3</td>
<td>5.1-6.0</td>
<td>4.0-5.0</td>
<td>&lt;4.0</td>
<td></td>
</tr>
<tr>
<td>NAI = N x P x K x pH</td>
<td>0.05-0.32</td>
<td>0.0001-0.05</td>
<td>&lt;0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Particle Size (PS)</td>
<td>Particle size class</td>
<td>class</td>
<td>C,L,SCL,SL, SiC,LS, SiC,L, SiC,S,</td>
<td>C(%clay&gt;65), G,SC,AC,S</td>
<td></td>
</tr>
<tr>
<td>Soil Texture(TXT); CL=Clay Loam, SiC=Silty Clay, SiCL=Silty Clay Loam, C=Clay, L=Loam, SiL=Silty Loam, LS=Loamy Sand, SCL=Sandy Clay Loam, SL=Sandy Loam, S=Sand, G=Gravel Soil</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rooting Conditions (R)</td>
<td>Soil Depth</td>
<td>cm.</td>
<td>&gt;100</td>
<td>50-100</td>
<td>25-50</td>
</tr>
<tr>
<td>Topography (TOPO)</td>
<td>Landform and Slope</td>
<td>Class &amp; %</td>
<td>Table 1a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Remark:</td>
<td>Soil Texture(TXT); CL=Clay Loam, SiC=Silty Clay, SiCL=Silty Clay Loam, C=Clay, L=Loam, SiL=Silty Loam, LS=Loamy Sand, SCL=Sandy Clay Loam, SL=Sandy Loam, S=Sand, G=Gravel Soil</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 1a** Matrix of slope gradient and landform

<table>
<thead>
<tr>
<th>Slope (%)</th>
<th>Flood Plain</th>
<th>Low Terrace</th>
<th>Middle Terrace</th>
<th>High Terrace</th>
<th>Foot Slope &amp; Erosion Surface</th>
<th>Mountain &amp; Rock Outerop</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-2</td>
<td>N</td>
<td>N</td>
<td>S1</td>
<td>S2</td>
<td>S1</td>
<td>N</td>
</tr>
<tr>
<td>2-5</td>
<td>N</td>
<td>S1</td>
<td>S2</td>
<td>S3</td>
<td>S2</td>
<td>N</td>
</tr>
<tr>
<td>5-12</td>
<td>N</td>
<td>S2</td>
<td>S3</td>
<td>S3</td>
<td>S3</td>
<td>S</td>
</tr>
<tr>
<td>&gt;12</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Remark:</td>
<td>S1=1.0, S2=0.8, S3=0.4, N=0.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**b) Nutrient Availability Index (NAI)**

The "NAI", is based on the method developed by Radcliffe et al (1982) and is given by NAI = NxPxKxPH. The soil map of Land Development Department (LDD) provides information of N, P, K and pH, those of which were used in the overlay process to create the spatial layer of NAI. The sub-layers (N, P, K, and pH) were assigned the values of rating factor as given in the table 1. The values of rating of the NAI are also given in the table 1.

**c) Particle Size (PS)**

The "PS" includes soil texture and coarse surface materials on which is important edaphic constraint for the sugar-cane. The PS is defined as class of the particle size. The values of rating factor of the particle size were given in the table 1.

**d) Rooting condition (R)**

The "R" land quality layer was determined using the soil depth. Available soil map was used to assign this factor rating for the evaluation.

**e) Topography (TOPO)**

The topography layer is a matrix of slope gradient and landform. The map of the slope and landform combination was digitally established and values assigned were given as in sub-table 1a.

Each of the defined land qualities with their associated attribute was digitally encoded in GIS database to create five thematic layers.
3.4 Land Suitability

The evaluation model for sugar-cane was given using the values of the factor rating as follows:

\[ \text{Suitability} = W \times \text{NAI} \times \text{PS} \times \text{R} \times \text{TOPO} \]

These thematic layers were integrated by spatially overlaying each with the suitability model of the defined 5 layers. (Fig. 2) The output layer yields 4 classes: S1=highly suitable, S2=moderately suitable, S3=marginally suitable and N=unsuitable. The validation of the model was made, based on the field investigation of the crop yield.

![Figure 2. The process of studying land suitability for sugarcane.](image)

4. RESULTS AND DISCUSSIONS

4.1 The Suitability Map

The suitability map resulting from the spatial overlay of land qualities for sugar-cane is shown in figure 3. The suitability area in addition to the map is shown in table 2. The suitability areas cover 10.94, 20.20, 12.43, 43.00, 11.68 and 1.74% for highly suitable, moderately suitable, marginally suitable, unsuitable, unclassified (conservation and built up) and water body respectively. The study provides an approach to identify parametric values in modeling the land suitability for sugar-cane. We provide the overall insight into the land qualities affecting the suitability of land spatially and quantitatively. The result indicated that the highly suitable lands are found on the soils inherently fertile, high availability of water with favorable physical landscape.

4.2 Model Validation

To validate the result reliability, sixty-seven plots with different suitabilities were superimposed on the map. The result was shown in table 3 with overall accuracy of 86.57% and kappa coefficient of 0.786.
Table 2  Land suitability for sugarcane in the Northeast, Thailand

<table>
<thead>
<tr>
<th>Land suitability classes</th>
<th>Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highly suitable (S1)</td>
<td>10.94</td>
</tr>
<tr>
<td>Moderately suitable (S2)</td>
<td>20.20</td>
</tr>
<tr>
<td>Marginal suitable (S3)</td>
<td>12.43</td>
</tr>
<tr>
<td>Unsuitable (N)</td>
<td>43.00</td>
</tr>
<tr>
<td>Unclassified area</td>
<td>11.68</td>
</tr>
<tr>
<td>Water Body</td>
<td>1.74</td>
</tr>
<tr>
<td>Total area</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Table 3  Confusion matrix

<table>
<thead>
<tr>
<th>Ground Truth</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>N</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>7</td>
<td>6</td>
<td>-</td>
<td>-</td>
<td>13</td>
</tr>
<tr>
<td>S2</td>
<td>-</td>
<td>32</td>
<td>-</td>
<td>-</td>
<td>32</td>
</tr>
<tr>
<td>S3</td>
<td>-</td>
<td>3</td>
<td>14</td>
<td>-</td>
<td>17</td>
</tr>
<tr>
<td>N</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>7</td>
<td>41</td>
<td>14</td>
<td>5</td>
<td>67</td>
</tr>
</tbody>
</table>

Kappa = 0.786

Figure 3. Land suitability for sugarcane.
5. REFERENCES

RECENT DROUGHT IN NE THAILAND: REGIONAL VEGETATION DYNAMICS AND NDVI-RAINFALL RELATIONSHIPS

Piychat RATANA¹², Nagon WATTANAKIJ¹ and Charat MONGKOLSAWAT¹
¹Center of Geo-informstics for the Development of Northeast Thailand, Khon Kaen University, Thailand
²Department of Geotechnology, Faculty of Technology, Khon Kaen University, Thailand
tel: 66-43-362125  FAX: 66-43-362126
e-mail: piyrat@kku.ac.th

KEY WORDS: Drought, MODIS, NDVI, time series

ABSTRACT: Northeast Thailand is the driest region in Thailand with a severe drought problem persisting for more than a decade. The impact of the drought on economy, environment and social well being is widely recognized and reported upon. Despite the importance of monitoring drought, most of previous studies have focused on drought risk and database creation. Therefore, to improve knowledge on vegetation response to precipitation at regional scale for drought monitoring, the objectives of this study were to determine the relationships between satellite-derived NDVI and rainfall over NE Thailand region, and to investigate the overall vegetation dynamics and inter-annual responses. Seven years (2000-06) of MODIS 16-day composite NDVI at 250m resolution and seven years (2000-06) of precipitation data from over 300 stations were used in this study. Spatial rainfall and NDVI anomalies as well as time lag relationships between rainfall and NDVI were analyzed. Results showed downward trends in 7-year NDVI temporal profiles with negative anomalies in rice, crops, orchards, and deciduous forest. This suggests that the impact of drought on vegetation can be seen in satellite observations. We found strong relationships between rainfall and one-month lag NDVI over the region. More detailed studies on the seasonal dynamics and rainfall relationships for major land cover types i.e. rice, crops, and forests are needed to improve drought monitoring and impact assessments.

1. INTRODUCTION

Droughts, a part of the earth’s climate, are abnormally dry and hot weather when there is shortage of water. It is difficult to determine onset and the end of drought. The duration of drought can be weeks, months, or even last long for years. However, the first evidence can be seen in rainfall record. Drought brings a hardship to people in that area and effects to the whole country or region, and even the whole world. Impacts from drought can cause many problems to natural and climate system and human activities by reducing social well-being.

Meteorological data such as precipitation, surface temperature, and soil moisture, have been used for drought assessment. In agricultural drought, soil water deficiency and plant water stress are highly considered. Vegetation responds to climate and soil environments
to meet their requirements of water, sunlight, carbon dioxide, temperature and nutrient. It is stated that the vegetation water stress for all the species turns out to be very similar (Laio, et. al., 2001a; 2001b).

Satellite remote sensing has been found to be useful for earth observation. Many satellite-based indices were established for terrestrial biosphere monitoring. Vegetation Indices (VIs), measures of greenness, have been used for vegetation health condition and change detection. The Normalized Difference Vegetation Index (NDVI) is the most common VI that is sufficiently stable to permit meaningful comparisons of seasonal, inter-annual, and long-term variations of vegetation structure, phenology, and biophysical parameters (Tucker & Sellers, 1986). More than a decade, AVHRR-NDVI data have been utilized for climate and environmental changes including drought monitoring and climate impact assessment at regional and global scales (Kogan 1993; 1997; Ungania, 1998; Ji & Peters, 2003; Singh et al., 2004; Ramesh et al., 2003). Based on NDVI, the vegetation Condition Index (VCI) was developed to separate the short-term weather signal in the NDVI data from the ecological signal. It was found the usefulness of VCI for drought detection, tracking, mapping, and estimating drought impact on vegetation (Kogan, 1995).

The objective of this study was to investigate on recent drought in NE Thailand on regional vegetation dynamics and NDVI-relationships.

2. STUDY SITE

In Northeast Thailand, drought has the most profound effect on the way of living and regional economy. It is also a major menace to regional food supplies. By its severity and duration these events can be disastrous not only locally but for the whole economic structure. The Northeast of Thailand is located between latitude 14° 14´ to 18° 27´ and longitude 101° 15´ to 105° 35´ (Figure 1). The annual precipitation is ~1,300 mm/year with 6-moth wet season period from May to October. Average temperature is ~26.9 °C.

Figure 1 Northeast region (grey), Thailand.
3. DATA AND METHODS

The Moderate Resolution Imaging Spectroradiometer (MODIS), well-calibrated sensor was recently launched in December 1999. Seven years (2000-06) of MODIS 16-day composite NDVI at 250m resolution and seven years (2000-06) of precipitation data from over 300 stations were used in this study.

Vegetation indices are spectral transformations developed to measure vegetation “greenness”. The NDVI is a normalized ratio between near infrared reflectance ($\rho_{\text{nir}}$) and red reflectance ($\rho_{\text{red}}$), has been widely used in satellite-based vegetation monitoring and modeling,

$$\text{NDVI} = \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + \rho_{\text{red}}}$$

Although the NDVI has been extensively used in the past for vegetation monitoring, it is often very difficult to interpret in relation to vegetation condition, especially when comparing different ecosystems. From the NDVI alone, one cannot isolate weather related NDVI changes from other changes related to geographic factors such as soils, topography, vegetation type and climate. To separate the short-term weather signal in the NDVI data from the ecological signal Kogan (1990) proposed the Vegetation Condition Index (VCI),

$$\text{VCI}_i = \frac{\text{NDVI}_i - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}} \times 100$$

where the absolute minimum and maximum NDVI values during the 2000-2007 record.

Seasonal profiles were generated from 7-years (2000-2006) MODIS 16-day composite data over NE Thailand region. Monthly VCI values were computed from the year 2000-2006 NDVI data. Spatial rainfall and NDVI anomalies as well as time lag relationships between rainfall and NDVI were analyzed.

4. RESULTS AND CONCLUSION

Temporal profile NE Thailand showed downward trend in 7-year NDVI temporal profiles (Figure 2). Results also showed negative anomalies in rice, crops, orchards, and deciduous forest. This suggests that the impact of drought on vegetation can be seen in satellite observations.
The VCI values range from 0 to 100. Low values of VCI indicate stress or poor vegetation condition, possibly related to the impact of drought, whereas high values would suggest the good vegetation condition. Figure 3, in late 2003 to early 2004 and late 2004 to early 2005, poor condition of vegetation, low VCI (red), was found which was concurrent with lower precipitation.

![Figure 3. The 7-year (2000-2006) monthly MODIS VCI](image)

We found strong relationships between rainfall and one-month lag NDVI over the region (Figure 4). More detailed studies on the seasonal dynamics and rainfall relationships for major land cover types i.e. rice, crops, and forests are needed to improve drought monitoring and impact assessments.
5. ACKNOWLEDGEMENT

This work was supported by Geo-informatics Center of the Development of Northeast Thailand, Khon Kaen University, Thailand.

6. REFERENCES

RECENT DROUGHT IN NE THAILAND: CASE STUDY USING MODIS TIME SERIES

Piyachat RATANA¹,²
Instructor, ¹Department of Geotechnology, Faculty of Technology, ²Geo-informatics Centre for the Development of Northeast Thailand, Khon Kaen University
123 Maliwon Rd., Maung, Khon Kaen, Thailand 40000
Tel: (66) 43-362-125 Fax: (66) 43-362-126
E-mail: piyrat@kku.ac.th

KEY WORDS: Drought, MODIS, Thailand, Vegetation Index, time series

ABSTRACT: Drought is one of the most serious problems in Northeast Thailand with far-reaching environmental and socio-economic impacts on local as well as the whole country. It is important to improve knowledge of landscape temporal variations and inter-annual vegetation response to precipitation at local to regional scales for drought monitoring and planning. With continuous spatial and temporal coverage, MODIS-derived enhanced vegetation indices (EVI) 16-day composite time-series data were utilized to monitor the vegetation seasonal dynamics and phenology of major land cover types including rice, crops (sugar cane and cassava), deciduous forest, and evergreen forest. Also, rainfall and satellite data anomalies were analyzed. Overall, temporal profiles of rice, crops, and deciduous forest depicted dry-wet seasonal contrast strongly coupled with rainfall with a pronounced dry season from November to April and wet season from May to October. In contrast, the evergreen forest showed the lowest seasonal contrast and relationships with rainfall with green-up occurring during the dry season (Jan-Feb). Significant decreasing trends were found in the 6-year (2001-06) MODIS EVI anomaly time series profiles for the rice, crops, and deciduous forests. However, the dominant land cover type, dry paddy rice, exhibited seasonal profiles with large spatial variations due to land use management practices, which resulted in more complex rainfall-vegetation relationship. Therefore, it is suggested that land use practices be taken into account for drought assessment and that the use of other land cover types, i.e. dryland crops be considered.

1. INTRODUCTION

One of the major problems in Northeast Thailand is drought. Drought has the most profound effect on environmental and socio-economic at local, regional and the whole country as well (Mongkolsawat et. al, 2001). Drought has lowered the water resources for drinking and irrigation as well as stressed vegetation including rice and other crops. There are also serious issues of mental health due to prolonged dry and hot weather periods. For drought monitoring and planning, it is needed to improved knowledge of landscape temporal variations and inter-annual behavior at local to regional scales.

Satellite remote sensing provides systematic and consistent observations of terrestrial vegetation dynamics. Satellite observations have been found to be a powerful tool to measure photosynthetic activity and phenology of vegetation at local- and regional-scales. With very high temporal resolution (daily acquisitions) over large regional coverage, the Moderate Resolution Imaging Spectroradiometer (MODIS) has been reported as an excellent sensor for terrestrial vegetation monitoring for of the land surface and vegetation health status on a local and global basis (Field et al., 1995; Potter et al., 1993; Goward et al., 1994).
Vegetation indices (VIs) were designed to enhance and quantify the “green” photosynthetic signal. The VIs have been used successfully for studies of vegetation activity, seasonal and inter-annual behavior, land cover classification, change detection (Townshend et al. 1991), phenology events (Schwartz & Reed, 1999; Huet et al, 2006) and drought monitoring (Tucker & Choudhury 1987; Kogan 1997; Bell et al. 1999). Over past few decades, vegetation indices have been widely used in terrestrial monitoring and satellite-based biosphere modeling (Potter et al., 1993). Furthermore, satellite-derived VIs have been used to monitor causes and effects of drought. The Enhanced Vegetation Index (EVI) was developed to optimize the vegetation signal and reduce soil background noise and is more responsive to canopy architecture and structural variations (Huete et al. 2002). The EVI has been reported to be responsive to canopy structural variations, including plant physiognomy, canopy type, canopy architecture, and leaf area index (LAI) (Huete et al., 1997; 2002).

3. OBJECTIVE

Drought impacts have important environmental consequences with important economic consequences on local and regional. Therefore, improved knowledge of landscape seasonal variations at local and regional scales is needed for monitoring and planning drought events. It is hypothesized that various land cover types will be affected and respond differently to drought. Therefore, the objective of this study will be to investigate spatial and temporal characteristics and variations of satellite data in Northeast Thailand as a function of land cover types using MODIS data for the recent drought.

4. STUDY SITES AND METHODS

4.1 Study Sites

The Northeast of Thailand is located between latitude 14° 14’ to 18° 27’ and longitude 101° 15’ to 105° 35’, approximately one-third of the whole country (Figure 1). The annual rainfall of the region ranges from 1,000 to 2,000 mm/year, with higher average rainfall in the north and northeast parts. In this region, wet season is about 6 months long, May to October. Average temperature is ~26.9 °C with maximum temperatures in April. In this region, land surface heterogeneity is high in Northeast Thailand and includes agricultural areas, pastures, savanna and forests. Major land cover types are paddy filed, crops (i.e. sugar cane and cassava), and deciduous and evergreen forests. MODIS EVI temporal data were extracted over local sites including rice, sugar cane, and cassava, deciduous forest, and evergreen forest. These sites were known conditions (field visited), located at Mahasarakham, Buriram, Ubon Ratchathani, and Nakorn Ratchasima, Surin, and Loei Provinces.

![Figure 1. Northeast Thailand, Thailand](image-url)
4.2 Data and Methods

For measuring temporal variations in “greenness” of different land cover types in Northeast Thailand, MODIS VIs time-series data were utilized over the local sites. The EVI optimizes the vegetation signal and reduced atmospheric and soil background noise,

\[
\text{EVI} = 2.5 \times \left[ \frac{(\rho_{\text{NIR}} - \rho_{\text{red}})}{(\rho_{\text{NIR}} + (6\times\rho_{\text{red}}) - (7.5\times\rho_{\text{blue}}) + 1)} \right] \quad (1)
\]

where \(\rho_{\text{NIR}}\) is NIR reflectance, \(\rho_{\text{red}}\) is red reflectance, \(\rho_{\text{blue}}\) is blue reflectance, 6 and 7.5 are atmosphere resistance coefficients, 1 is a canopy background brightness correction factor, and the gain factor is 2.5 (Huete et al., 1997; 1994).

The MODIS EVI product is computed from atmosphere corrected and cloud filtered surface reflectances and is composited over 16-day time intervals. In this study, quality assurance (QA) metrics were utilized to further filter and reduce cloud contaminated pixels. Vegetation seasonality was analyzed with 6-years (2001-06) of 16-day composite EVI time series at 1km resolution (MOD13A2) over local sites, encompassing the rice fields, the sugar cane and cassava fields, and the deciduous and evergreen forests.

Point-based long-term rainfall data over the region were collected from the Thai Meteorological Department (http://www.tmd.go.th/). Monthly precipitation values for anomaly analyses were computed from 30-year stationary records.

Satellite and rainfall data anomalies were analyzed using long-term point-based monthly and annual rainfall records and year 2000-06 MODIS EVI data. Correlations of rainfall and EVI were analyzed using simple regression method.

5. RESULTS AND CONCLUSIONS

5.1 Results

The anomalies in precipitation for year 2001-06 were computed from 30-years point-based rainfall records. Negative anomaly from year 2001 to 2006 was found. As well, there were downward trends in 6-year EVI temporal profiles with negative anomalies in rice, crops, and deciduous forest (Figure 2). This suggested that the impact of drought on vegetation can be seen in MODIS EVI observation.

The seasonal dynamics across the major land cover types, rice, sugar cane, cassava, deciduous, and evergreen forest sites were plotted and analyzed with MODIS, 1km resolution 16-day composite VI profiles for years 2001-06. Overall, temporal profiles of rice, sugar cane, cassava, and deciduous forest depicted dry-wet seasonal contrast strongly coupled with rainfall with a pronounced dry season and wet seasons (Figure 2). During the rainy season, May through October, high vegetation activity can be seen. For the dry-down phase of the dry season, November through April, EVI values decreased. However, differences in EVI seasonal profiles were apparent among evergreen forest and other land cover types (Figure 3). The evergreen forest showed the lowest seasonal contrast with high EVI values throughout the year. The green-up occurred during the dry season (~ February) and reached the “green” peak of growing season in June-July.
Figure 2. Six-years MODIS EVI temporal profiles over rice, sugar cane, cassava, deciduous forest, and evergreen forest sites.

The temporal profiles of all cover types showed distinct differences. Variations of vegetation seasonal behaviors (i.e. peak time and value and rate of increasing “greenness”) of rice, crops and deciduous forest were observed. The rice seasonal profile in Figure 3 showed a decrease in EVI values at the onset of the dry season (November) as well as an increase in EVI following the initiation of rainy season (May) and with the time lag of 2 months of the sugar cane and cassava. The EVI peaks were found in September-October (~0.46), September (0.42), July (0.40), and September-October (~0.39) for rice, sugar cane, cassava and deciduous forest profiles respectively. However, the lowest EVI value of the rice was fairly similar to those of crops and deciduous forest (~0.22), which occurred in February. In addition, the rice profile depicted the highest rate in growing season (steeper slope, Figure 3).

Figure 3. MODIS MOD13A2, 1km resolution, six-year monthly average land surface seasonal profiles over rice, sugar cane, cassava, deciduous forest, and evergreen forest sites.

From simple regression between rainfall and EVI, there were positively correlated between at the rice, sugar cane and cassava, and deciduous forest sites with fairly similar slopes. This suggests that water is an important controlling factor for vegetation in NE Thailand.

Figure 4. Relationships between EVI and rainfall at rice, sugar cane, cassava, deciduous forest sites.
5.2 Conclusions

MODIS time series dataset was able to monitor impact on drought. Drought-induced reduced in vegetation photosynthesis can be seen in the EVI temporal profiles. Decreasing trend of EVI values over 6-years data were found over major land cover types including rice, crops (sugar cane and cassava), and deciduous forest.

Strong pronounced dry-wet “greenness” values due to seasonal vegetation responses were found in this study. The rice, sugar cane, casava and deciduous forest seasonal profiles were driven by water. These agricultural and deciduous forest sites showed the highest wet-dry seasonal contrast with a pronounced dry season from November to April and an increase in wet season from May to October. The evergreen forest seasonal profile showed the least variations and least impact from drought.

However, the dominant land cover type, dry paddy rice, exhibited seasonal profiles with large spatial variations due to land use management practices (Figure 5), which resulted in more complex rainfall-vegetation relationship. Therefore, it is suggested that land use practices be taken into account for drought assessment and that the use of other land cover types, i.e. dryland crops be considered.

![Figure 5](image)

**Figure 5.** Monthly temporal profiles of 6-years average MODIS 16-days composite.

6. ACKNOWLEDGMENT

Thanks to Mr. Oychai Sithihakotra, Ms. Chanada Ratana, and Ms. Pariya Ratana for helping fieldwork. This work was supported by Geo-informatics Center of the Development of Northeast Thailand, Khon Kaen University, Thailand.

7. REFERENCES