Modeling REDD+ Baselines using Mapping Technologies: A pilot study from Balpakram-Baghmara Landscape (BBL) in Meghalaya, India

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Abstract
Reducing Emissions from Deforestation and Forest Degradation (REDD+) has emerged as a prominent potential climate change mitigation measures which aims at conservation of forests to sequester carbon. A key task of a REDD+ project is determination of historical deforestation rates and patterns, as well as the proximate causes and underlying forces of such deforestation. This baseline mapping is critical for identification of future REDD+ project scenarios to conserve carbon. The study demonstrates the potential use of mapping technologies like satellite remote sensing and Geographic Information System (GIS) in modeling REDD+ baselines for Balpakram-Baghmara Landscape (BBL) in Meghalaya, north-east region of India. The landscape is characterized by rapid deforestation and forest degradation. Temporal satellite remote sensing data of 1991, 2000 and 2011 were used to assess spatio-temporal patterns of forest cover changes. Based on quantitative analysis of the changes (1991-2011) deforestation rate was estimated to be 2.35% annually. Spatio-temporal datasets along with biotic and abiotic variables provide opportunities to model forest cover change further. Land Change Modeller (LCM) was used to predict forest cover status for 2021and 2031 using current disturbance scenarios. Comparing actual land-use land-cover (LULC) of 2011 with the predicted LULC of 2011 validated change prediction model and agreement was 65.22%. Expansion in cropland area, which has increased more than five times, has been the major force behind continuing forest loss.

1. Introduction

Widespread and growing concern on the threats posed by climate change to world's ecosystem (IPCC, 2007) has led to extensive international discussions, negotiations and agreements (Gorte, 2007). Responses to this concern have largely focused on reducing emissions of greenhouse gas (GHG) especially carbon dioxide, and on measuring carbon absorbed by and stored in forests, soils and oceans (Gorte, 2007). Deforestation and forest degradation in the tropics accounts for about 20% of global GHG emissions and constitute the majority of emissions from developing countries (IPCC, 2007 and Gullison et al., 2007). In this context reducing emissions from deforestation and forest degradation (REDD) has become an important potential mechanism of mitigating climate change as it is considered to be a cost-effective option (Kaimowitz, 2008, Aggarwal et al., 2009, Angelsen et al., 2009 and Ravindranath et al., 2012). Global forest sinks can contribute to one-third of the total abatement by 2050, with major contribution from avoided deforestation in tropical forest-rich countries (Tavoni et al., 2007). REDD is an effort to create a financial value for the carbon stored in forests, offering incentives for developing countries to reduce emissions from forested lands and invest in low carbon paths to sustainable development (http://www.unredd.org/AboutREDD/tabid/582/Default.aspx). Also the role of conservation, sustainable management of forests and enhancement of forest carbon stocks have been included in the concept of REDD+ currently being negotiated under the United Nations Framework Convention on Climate Change (UNFCCC) (Ravindranath et al., 2012). Despite having robust legislations, policies, programmes and institution India is still grappling with the issues of deforestation and degradation which adversely impacts livelihood of millions of people in the

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country (Aggarwal et al., 2009 and Ravindranath et al., 2012). Consequently there is large potential for REDD+ activities in the country. The 'Cancun Agreement' on REDD+ created a framework specifically listing the phased actions required from developing countries. As a part of the first phase or 'readiness phase' the countries are supposed to develop a national REDD+ plan or strategy (Ravindranath et al., 2012) to derive lessons and identify key issues and challenges in smooth implementation of REDD+. Hence it becomes imperative that India develops a few REDD+ pilots and incorporates lessons from these pilots in the national framework on REDD+. Development of LULC change maps and modelling future emissions based on historical trend rates and relationships between deforestation patterns and drivers of deforestation, guides a REDD project (Olander et al., 2008 and Clark Labs, 2010) and is termed as 'baseline mapping' (Clark Labs, 2010). Satellite remote sensing coupled with Geographic Information Systems are widely tested and suggested tools of analysing and modelling these spatio-temporal changes along with estimation of deforestation rates (Menon and Bawa, 1997, Giriraj et al., 2008 and Munsi et al., 2012). The north-east region of India has for long been able to retain a significant proportion of biodiversity including forest cover, possibly due to long years of isolation and difficult terrain, but now it is under increasing pressure to unleash its resources for economic development (Chatterjee et al., 2006). The old native forests of the Garo hills in western Meghalaya – one of the seven north-east Indian states – support one of the most diverse and luxuriant tropical vegetation in the world and majority of the forest patches are owned by the communities (Kumar et al., 2006a). In the context of REDD+ the present study was taken up to characterize the spatial and temporal patterns of changes in LULC particularly in forest cover, its rate of deforestation and to develop future scenarios using remotely sensed data in a case study area of Balpakram-Baghmara Landscape (BBL) in the Garo hills of Meghalaya. The region is characterized by rapid conversion of forest into agriculture, monoculture and mixed plantation and orchard farming, with potential threats of mining activities, which hampers the regeneration of vegetation. With this background the study was carried out with the objectives to (i) assess the magnitude and direction of LULC change using satellite images of 1991, 2000 and 2011; (ii) model the future LULC change pattern for 2021 and 2031; and lastly (iii) assess the agents of forest cover change.

2. Materials and Methodology

2.1 Study Area

BBL (Figure 1) falls in the South Garo Hills district of Meghalaya, spread over an area of 600 km^2 and comprises Balpakram National Park (220 km^2), Siju wildlife sanctuary (5.18 km^2), Baghmara Reserve forest (44.29 km^2) and community owned land (Kumar et al., 2006b and www.samrakshan.org/Eco.../Eco%20Tourism%20Brochure.pdf).

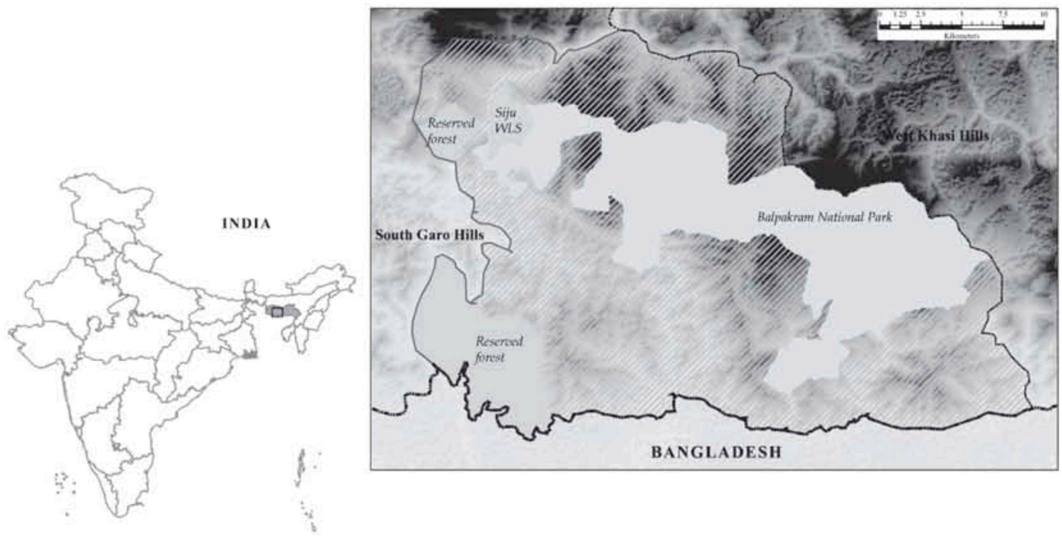

Figure 1: Map showing location of Balpakram-Baghmara Landscape

The reserved forest (RF), national park (NP) and wildlife sanctuary (WLS) which are under the control of the State Forest Department (Marcot et al., 2002), cover about 45 percent of the total study area and the remaining area belongs to the local communities. The Garo Hills as a whole are home to the indigenous *Garo* tribes (Kumar et al., 2006b). The *Garos* are of Tibeto-Burman stock and have an intricate clan based social organisation system (Ministry of Tourism, 2003). The winter is between November and March with a mean high of 25°C and low of 7°C. Summer is hot and humid and extends from April to October with maximum temperature of 37°C. Monsoon hits this region by end of April with an annual average rainfall that varies between 4000 mm to 11,436 mm (www.samrakshan.org/Eco.../Eco%20Tourism-%20Brochure.pdf). The protected areas (PAs) of the landscape support various forest types such as tropical moist evergreen forest representing undisturbed primary forests; tropical semi-evergreen forest or old secondary forests, i.e. 30 years or older forest growth; tropical moist deciduous forest or disturbed and relatively new secondary forests, i.e. younger to 30 years old forest growth; and grasslands that provide excellent habitats to many wildlife species (Kumar et al., 2010). The forest cover also boasts of tremendous faunal diversity with the landscape having one of the largest populations of the Asian Elephant (*Elephas maximus*) (Marcot et al., 2002 and Tiwari et al., 2005). Other important mammal species are the Clouded leopard, Hoolock Gibbon, large Indian civet, Bear macaque, and many others (www.samrakshan.org/Eco.../Eco%20Tourism%20 Brochure.pdf).Agriculture is the main occupation of the Garos and they practice shifting agriculture. Forest products play a vital role in the local economy and they are the main source of subsistence along with the agricultural produce (Barik and Darlong, 2007). The South Garo Hills district has the second highest forest cover in the state of Meghalaya; however there has been substantial loss in the last few years. Slash and burn shifting cultivation, locally known as *jhumming* or *jhum*, in which native people clear and burn the old forest growth over a piece of land to get fertile land for raising agricultural crops for one or two years and then move on to clear fresh forest land (Kumar et al., 2006b) is one of the major causes of forest degradation and loss in the landscape (Marcot et al., 2002 and Kumar et al., 2010). Thus, the area was selected to study the impact of such anthropogenic pressures on the forest cover.

2.2 Data Used

Satellite data of 1991, 2000 and 2011 along with Digital Elevation Model (DEM) and human disturbance parameters (proximity to road and settlements) were used to map and predict the changes in LULC. The orthorectified satellite data of Landsat TM of November 1991 and ETM+ of February 2000 for path and row 137/42 and 137/43 with spatial resolutions of 30 m were downloaded from the website www.landsat.org. IRS-P6 LISS III image of March 2011 for path and row 110/54 and 11/55 with spatial resolution of 23.5 m was procured from National Remote Sensing Centre, Hyderabad. The 2011 satellite data was geometrically corrected using image to image registration technique and was referenced to the UTM coordinate system (Zone 44), WGS 84 datum. The three time period satellite data were then subsetted to obtain the study area. DEM of the landscape area was downloaded from the Advanced Spaceborne Thermal Emission and Reflection (ASTER) Global DEM website http://www.gdem.aster.ersdac.or.jp/. State Forest Department reference maps were used to generate the ancillary database on road network and settlements. Three softwares were used in the study, viz. Arc GIS for paper map digitization, data overlay and map preparation, ERDAS Imagine for satellite image processing, and finally IDRISI Andes for change analysis and prediction modelling.

2.3 Land Use Land Cover Mapping

To eliminate the effect of varying spectral resolution of the input images, standard FCCs (false colour composite) were generated for land use mapping. The processed satellite images of 1991, 2000 and 2011 were on-screen visually interpreted and classified using unsupervised classification (ISODATA technique). The produced maps were compared with the respective satellite images and were cleaned by recoding. Separate AOIs were prepared for water body and built-up area and were recoded. After classification LULC datasets were re-sampled to 30 m cell size using nearest neighbourhood re-sampling method to minimize the effect of varying spatial resolution on area statistics and change analysis. Field verification of the final output was carried out to calculate the accuracy of 2011 LULC. Field survey was carried out in the post monsoon season. Random points were selected and at each location the existing LULC and the location information was recorded using Global Position System (GPS).

2.4 Change Analysis

For change analysis, Land Change Modeler (LCM) of IDRISI Andes was used. Changes in LULC were computed by comparing maps from two different timeline (1991-2000 and 2000-11) pixel by pixel to show the changes from one class to another. The generated change matrix was used to calculate the rate of change in each class in the mentioned timeline using the following compound interest formula (Puyravaud, 2003):

$$r = \frac{\ln(A_{t1}) - \ln(A_{t0})}{t1 - t0} \times 100$$

Equation 1

Where, *r* is the rate of LULC change, and A_{t0} and A_{t1} are the forest cover (km^2) at time t_0 and t_1 (year) respectively.

2.5Change Prediction

The road and settlement (vector) layers were converted to raster format. ASTER DEM was used to prepare slope and aspect maps. These five variable layers (road, settlement, DEM, slope and aspect) were converted to .rst format of IDRISI. Distance maps were prepared for road and settlement layers by calculating the Euclidean distance between the pixels and the target layer. BBL being a hilly area, impact of slope, aspect and elevation also play important role in LULC changes. All these layers prepared are continuous and quantitative. Apart from these variables, a sixth qualitative variable, which is empirical likelihood to change map was also prepared. For preparing this, a map showing changes from all LULC classes to built-up area was prepared. The map was changed to probability (0-1) using evidence likelihood transformation. It is based on the frequency of pixels of different categories to appear within the change area (Eastman, 2009). The explanatory powers of these variables were calculated by Cramer's V statistics. It calculates the strength of association between two variables. A Cramer's V of about 1.5 or higher is considered useful, while those of 0.4 or above are considered good (Eastman, 2009). Cramer's V is calculated using the following formula (Cramér, 1999):

$$V = \sqrt{\frac{\chi^2}{N\,(m-1)}}$$

Equation 2

Where, χ^2 = Chi-square; N = population; m = number of rows or columns in the table. The transition potential maps were prepared using the six variables as input, the transitions to be modelled were selected and the procedure was based on Multi-Layer Perceptron (MLP) neural network using Back Propagation (BP) algorithm. MLP is an artificial neural network that learns non-linear function mappings. A typical BP network contains one input layer, one or more hidden layers and one output layer (Gautam and Panigrahi, 2007 and Munsi et al., 2012). In this case the six explanatory variables were the input layers, and the transitions to be modelled were the output layers. When the nodes of an input layer receive information from an external source, they become activated and emit signals to the next layer such that each node of the input layer has an exclusive correspondence to every node in the next layer. These signals, in turn, pass to the output layer. Each connection between two nodes in adjacent layers is associated with weight coefficients, which adjust the signal strength based on the characteristic of input information. During BP training, an error is determined by comparing the calculated output with the desired output and the error is propagated back to the hidden and input layers in subsequent trainings. The training of the model is completed in a successive number of iterations when the change in error is sufficiently small (or less than the user defined limit) (Gautam and Panigrahi, 2007). After the completion of training in MLP, transition potential modelling is used to prepare transition maps. Each of these maps were given weight on the basis of transition probabilities obtained from Markov transition matrix (in this case 2021and 2031). The process analyzes two qualitative LULC images from different dates and produces a transition matrix, which determines the likelihood for a cell or pixel to change from one LULC class to every other from time 1 to time 2 (Eastman, 2009). On the basis of the transition probabilities hard prediction modeling was carried out. The hard prediction process is based on multi-objective land allocation (MOLA). It looks through all transitions and creates a matrix of host classes (classes that will lose some amount of land) and a list of claimant classes (classes that will acquire land) for each host (Eastman, 2009). Finally, the results of the reallocation of each host class are overlaid to produce prediction maps.

2.6 Validation

For validating the model, a LULC map was predicted for 2011. Then by using the VALIDATE module of IDRISI Andes, the predicted 2011 LULC was compared with the actual 2011 LULC. This module compares the two LULC maps and measures the agreement of cells and location of cells in each class (Eastman, 2009).

3. Results and Discussion

3.1 Land Use Land Cover Maps

Temporal LULC maps for 1991, 2000 and 2011 with 10 classes were prepared (Figure 2). The area was classified into very dense forest (VDF), moderately dense forest (MDF), open forest, shrub land, waterbody, cropland, abandoned jhum cultivation areas, current jhum cultivation areas, sand/barren/open land and built-up area. VDF refers to all lands of forest cover having canopy density of 70% and above, MDF refers to forested lands having canopy density between 40-70%, open forest is forested land with canopy density of 10-40% and scrub land are degraded forested lands having canopy density less than 10% (FSI, 2011). Cropland includes area under settled permanent agriculture, abandoned jhum cultivation areas refers to areas that have been left abandoned by the local community after being used for cultivation while current jhum cultivation areas are those where currently jhumming is practised. The temporal maps and the area statistics (Table 6) ascertained that VDF and MDF have decreased over the time, which is due to their conversion to open forest and scrub land. Though open forest increased during 1991 and 2000 it witnessed a decrease between 2000 and 2011. This can be largely attributed to deforestation and degradation initially but depletion in the last decade, as a result scrub land continued to increase. Area under cropland, abandoned jhum cultivation and current jhum cultivation expanded in both the time period due to increasing anthropogenic conversion of mature and primary forests to jhum land. For agricultural purposes, all culturable land is being used either for settled permanent agriculture or jhumming (Kumar et al., 2006b). The area under built-up also witnessed a constant increase from 1991 to 2011 as land in Garo Hills is mainly used for residential and agricultural purposes by society (Kumar et al., 2006b). The data collected from field was used to calculate the accuracy of 2011 LULC map using the common 'confusion matrix' method (Zhou et al., 2004). The overall accuracy of the map was 80.05% with a Kappa coefficient of 0.79.

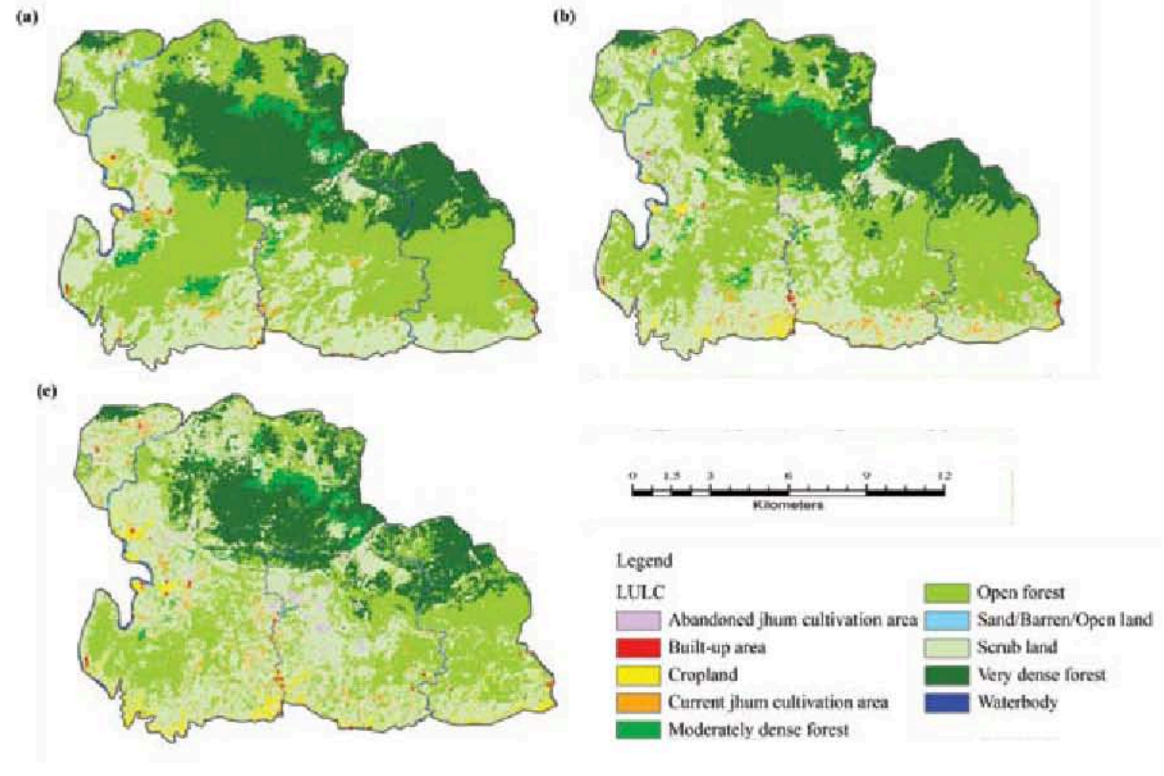

Figure 2: Land use land cover maps for 1991(a) 2000 (b) and 2011 (c)

Table 1: Change matrix for 1991-2000 (area in km2)

1991	2000									
	VDF	MDF	OF	SL	WB	CL	AJC	OL	BA	CJC
VDF	109.06	1.14	28.71	3.47	0.00	0.00	0.00	0.00	0.00	0.00
MDF	0.00	12.92	6.25	6.81	0.00	0.00	0.00	0.00	0.00	0.00
OF	0.00	0.00	217.17	49.05	0.00	0.00	0.00	0.00	0.00	0.47
SL	0.00	0.00	0.00	119.91	0.00	4.69	0.00	0.00	0.14	4.50
WB	0.00	0.00	0.00	0.00	4.37	0.00	0.00	0.00	0.00	0.00
CL	0.00	0.00	0.00	0.00	0.00	2.42	0.00	0.00	0.08	0.00
AJC	0.00	0.00	0.00	0.91	0.00	1.13	6.41	0.01	0.15	0.00
OL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.74	0.01	0.00
BA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93	0.00
CJC	0.00	0.00	0.00	0.00	0.00	0.00	0.31	0.00	0.00	0.24

VDF – very dense forest; MDF – moderately dense forest; OF– open forest; SL – scrubland; WB = waterbody; CL – cropland; AJC – abandoned jhum cultivation area; OL – open land/barren land; BA – built-up area; CJC – current jhum cultivation area

Table 2: Change matrix for 2000-2011 (area in km2)

2000	2011									
	VDF	MDF	OF	SL	WB	CL	AJC	OL	BA	CJC
VDF	108.54	1.29	33.05	5.33	0.00	0.00	0.00	0.00	0.00	0.00
MDF	0.00	12.23	1.63	8.51	0.00	0.00	0.00	0.00	0.00	0.00
OF	0.00	0.00	141.93	93.12	0.00	0.00	0.00	0.00	0.00	1.72
SL	0.00	0.00	0.00	133.62	0.00	8.65	0.00	0.00	0.21	5.25
WB	0.00	0.00	0.00	0.00	4.37	0.00	0.00	0.00	0.00	0.00
CL	0.00	0.00	0.00	0.00	0.00	7.54	0.00	0.00	0.08	0.00
AJC	0.00	0.00	0.00	3.63	0.00	1.16	6.99	0.02	0.17	0.00
OL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.71	0.03	0.00
BA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.94	0.00
CJC	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00	1.04

VDF – very dense forest; MDF – moderately dense forest; OF– open forest; SL – scrub land; WB = waterbody; CL – cropland; AJC – abandoned jhum cultivation area; OL – open land/barren land; BA – built-up area; CJC – current jhum cultivation area

Table 3: Rate of land use/land cover change

LULC class	Rate of change	
	1991 - 2000	2000 - 2011
Very dense forest	-1.02	-0.02
Moderately dense forest	-2.06	-0.15
Open forest	0.04	-1.41
Scrub land	0.57	1.20
Water body	-0.82	0.07
Cropland	5.02	2.94
Abandoned jhum cultivation area	6.79	0.29
Sand/Barren/Open land	-0.47	-0.03
Built up area	0.27	0.35
Current jhum cultivation area	1.41	1.70

3.2 Change Analysis

Post-classification comparison method, which is the most common approach in change detection studies, has been applied in this study. Change matrix (Table 1 and Table 2) represents the area that has undergone transition. The diagonal cells of the matrix represent the area that has remained under same class in both the time periods, whereas the non-diagonal elements represent transitions from one class to another. VDF area has mostly converted to open forest due to forest degradation and selective deforestation. During 1991-2000, MDF area also got transformed to open forest however in the later decade (2000-11) it was mostly converted to scrub land. Area under open forest, on the other hand got transitioned to built-up area and current jhum cultivation area. Scrub land area witnessed similar transitions and was also converted to cropland. Due to mass scale practice of jhumming over centuries, the larger tracts of primary forest cover have been fragmented into a number of secondary forest patches (Kumar et al., 2010) during both the time periods. Conversion of current jhum cultivation area to abandoned jhum is an indication of the continuing age-old practice of shifting cultivation. Built-up area increased over time as it gained area from scrub land, cropland, abandoned jhum cultivation area and open land. Growing population necessitated expansion of built-up areas. The calculated change rate (Table 3) represents increased rate of deforestation and degradation in VDF and MDF. Open forest which increased at positive rate in the initial decade (1991-2000) witnessed a decline during 2000-11 due to degradation in the initial phase and deforestation in the later part of the study period. Scrub land expanded at a positive growth rate during both the periods, an indication of the continuing forest degradation. Cropland, current jhum cultivation, abandoned jhum cultivation and built-up areas showed positive growth rate. This is mainly because of the increasing anthropogenic pressures in the landscape particularly shifting cultivation (Kumar et al., 2006a).

3.3 Change Prediction

Markov transition probabilities for 2021 and 2031 are given in Tables 4 and 5 respectively. The diagonal cells represent the probability that an area will remain under the same class. By comparing the two matrices, it can be concluded that probability of VDF remaining in the same class has reduced in the next time period (2031). It has the highest probability of getting converted to open forest which in turn is most likely to get converted into scrub land. The impact of human activities on forest cover has accentuated further because of high rainfall and hilly terrain as a result the forests are getting fragmented (Government of Meghalaya, 2005). The contribution to expanding cropland and current jhum cultivation area comes mainly from scrubland. The likelihood of scrubland, cropland, abandoned jhum cultivation area and open land getting transformed to built-up areas has increased over time. Comparing predicted 2011 LULC map and actual 2011 LULC map validated the model. This gave an accuracy of 65.22%, which is acceptable as the number of classes is high and accuracy decreases with increasing number of class (Munsi et al., 2012). The LULC maps of 2021 and 2031 (Figure 3) are product of hard prediction model and show probable spatial distribution of various land cover classes.

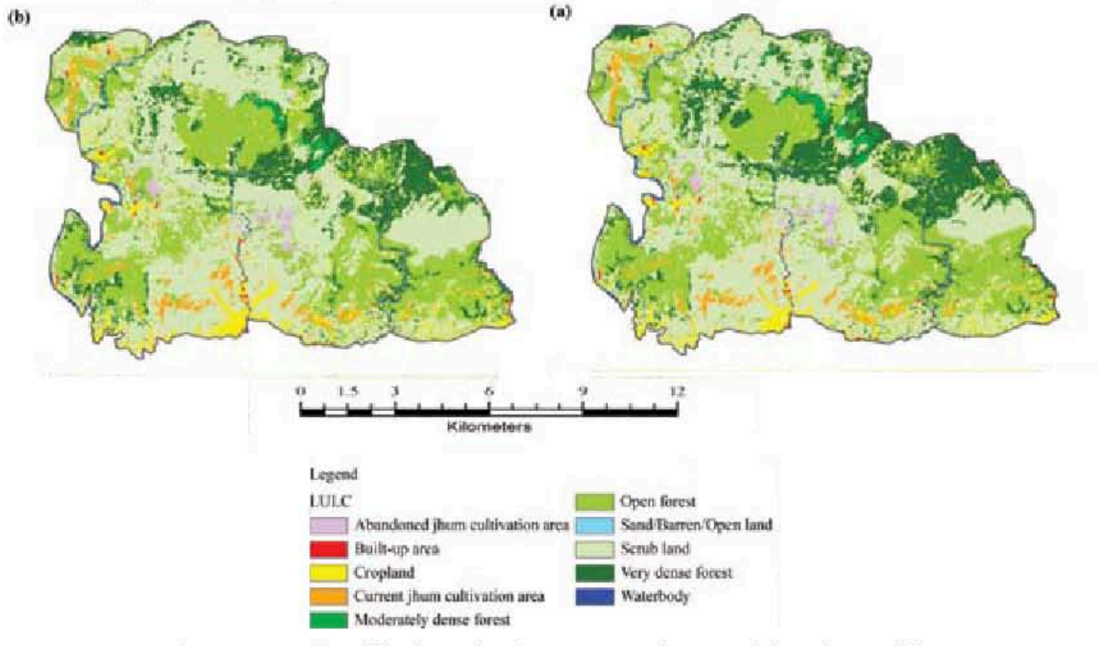

Figure 3: Predicted land use land cover maps for 2021 (a) and 2031 (b)

Table 4: Markov transition probabilities for 2021

2011	2021									
	VDF	**MDF**	**OF**	**SL**	**WB**	**CL**	**AJC**	**OL**	**BA**	**CJC**
VDF	0.49	0.02	0.51	0.02	0.00	0.00	0.00	0.00	0.00	0.00
MDF	0.00	0.51	0.11	0.09	0.00	0.00	0.00	0.00	0.00	0.00
OF	0.00	0.00	0.43	0.38	0.00	0.00	0.00	0.00	0.00	0.07
SL	0.00	0.00	0.00	0.30	0.00	0.09	0.00	0.00	0.08	0.12
WB	0.00	0.00	0.00	0.00	0.95	0.00	0.00	0.00	0.00	0.00
CL	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.05	0.00
AJC	0.00	0.00	0.00	0.01	0.00	0.01	0.08	0.02	0.02	0.00
OL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.25	0.00
BA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.75	0.00
CJC	0.00	0.00	0.00	0.00	0.00	0.04	0.08	0.00	0.09	0.21

VDF – very dense forest; MDF – moderately dense forest; OF– open forest; SL – scrubland; WB = waterbody; CL – cropland; AJC – abandoned jhum cultivation area; OL – open land/barren land; BA – built-up area; CJC – current jhum cultivation area

Table 5: Markov transition probabilities for 2031

2021	2031									
	VDF	MDF	OF	SL	WB	CL	AJC	OL	BA	CJC
VDF	0.40	0.00	0.57	0.04	0.00	0.00	0.00	0.00	0.00	0.00
MDF	0.02	0.46	0.22	0.12	0.00	0.00	0.00	0.00	0.00	0.00
OF	0.00	0.00	0.39	0.40	0.00	0.00	0.00	0.00	0.00	0.09
SL	0.00	0.00	0.00	0.27	0.00	0.11	0.00	0.00	0.00	0.15
WB	0.00	0.00	0.00	0.00	0.97	0.00	0.00	0.00	0.00	0.00
CL	0.00	0.00	0.00	0.00	0.00	0.59	0.00	0.00	0.09	0.00
AJC	0.00	0.00	0.00	0.01	0.00	0.02	0.09	0.05	0.04	0.00
OL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.32	0.00
BA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.77	0.00
CJC	0.00	0.00	0.00	0.00	0.00	0.06	0.14	0.00	0.13	0.19

VDF – very dense forest; MDF – moderately dense forest; OF– open forest; SL – scrubland; WB = waterbody; CL – cropland; AJC – abandoned jhum cultivation area; OL – open land/barren land; BA – built-up area; CJC – current jhum cultivation area

Table 6: Area statistics of LULC classes

LULC class	**1991**		**2000**		**2011**		**2021 (predicted)**		**2031 (predicted)**	
	Area (km^2)	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**
VDF	134.15	22.97	109.06	18.68	108.54	18.59	91.75	15.71	76.50	13.10
MDF	22.96	3.93	14.06	2.41	13.52	2.31	8.66	1.48	5.30	0.91
Open forest	249.84	42.78	252.13	43.17	176.61	30.24	165.27	28.30	159.73	27.35
Scrub land	159.97	27.39	180.16	30.85	244.21	41.82	255.11	43.68	271.01	46.41
Water body	4.37	0.75	4.37	0.75	4.37	0.75	4.36	0.75	4.36	0.75
Cropland	2.91	0.50	8.24	1.41	17.35	2.97	28.43	4.87	37.70	6.46
Abandoned jhum	1.65	0.28	6.72	1.15	7.24	1.24	9.89	1.69	9.37	1.60
Open land	3.04	0.52	2.75	0.47	2.73	0.47	2.70	0.46	2.71	0.46
Built-up area	1.23	0.21	1.30	0.22	1.42	0.24	1.52	0.26	1.63	0.28
Current jhum	3.89	0.67	5.21	0.89	8.00	1.37	16.29	2.79	15.69	2.69

The predicted maps showed that if the current probability of change persists, only 13.1% of the total area would remain under VDF while area under scrub land would increase to 46.42% (Table 6). Cropland area is likely to expand more than current jhum cultivation area as the region is undergoing slow transition to settled cultivation. Vegetable production and horticulture is one of the most important emerging livelihood activities in Meghalaya (Barik and Darlong, 2007) and BBL is also experiencing similar trend. The increase in built-up area will be comparatively less primarily because of the landscape terrain.

4. Conclusion

The study analysed LULC distribution for three decades and based on the past and present probabilities of changes predicted the future (2021 and 2031) land cover distribution, in BBL to establish REDD+ baseline scenario. Based on change analysis from 1991 to 2000 and 2011 the annual deforestation rate was calculated to be 2.35% per year. The entire landscape has undergone massive deforestation and forest degradation in the last two decades. The VDF cover has decreased almost by 53.24% over a period of 20 years (1991-2011), and as per the predicted scenario will experience further loss by 2031. The probability of VDF getting converted to open forest is likely to increase from 0.51 in 2021 to 0.57 in 2031. Similar trend can be seen in MDF cover. Whereas area under scrub land increased by 52.66% during 1991-2011 and is likely to increase further by 10.97% in the next 20 years (2031). Also the probability of conversion of scrubland into cropland and current jhum cultivation areas would also increase over time suggesting increasing human interference in the landscape area. The underlying driving forces for deforestation are basically unavailability of land for small-scale farming as well as orchard farming. The whole landscape is hilly and some of the fertile areas are at very high altitude making it difficult for farming. In the absence of other viable alternatives, the majority of the population continue to depend on shifting cultivation (Barik and Darlong, 2007 and Government of Meghalaya, 2005) which is being practiced in revenue, reserve and protected forests also (Government of Meghalaya, 2005). Shortening of jhum cycles is another important factor (Datta-Roy et al., 2009) leading to loss of protective and productive vegetation cover. Historically, the jhum cycle, the intervening fallow period between two cropping periods, was long ranging from 50 to 60 years. Now it has been reduced to 1-3 years in the central and eastern parts of the state (where BBL is located) due to increasing population and pressure on land. This is alarmingly short for the recovery of the soil fertility level, leading to progressive fertility loss and extensive land degradation (Government of Meghalaya, 2005). Moreover increasing need for subsistence farming (Barik and Darlong, 2007) or settled cultivation has led to additional pressure on forested land resulting in degradation. The other deforestation and degradation agent that is posing to be a potential threat to forest of the landscape is expansion of mining activities (Datta-Roy et al., 2009 and Government of Meghalaya, 2005). Thus it can be concluded from the study that the historical trend of LULC change is assumed to continue in the landscape area as all the drivers and agents of deforestation and degradation are equally active in BBL and there is no indication that this scenario will change in near future. Baseline mapping and future scenario modeling are two important aspects of an entire REDD+ project. Development of baseline scenario to a great extent depends on the accuracy of historical image analysis. GIS and remote sensing are comprehensive tools capable of reviewing the historical land cover change of the area, interpretation and analysis of the trends, identification of drivers of deforestation and incorporation of such drivers in map form to model the potential future scenarios. These tools can greatly reduce the time and cost in development of deforestation baseline, which currently is delaying the finalization of project development for many prospective REDD+ projects.

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References

Aggarwal, A., Das, S. and Paul, V., 2009, Is India Ready to Implement REDD Plus?- A Preliminary Assessment. The Energy and Resources Institute (TERI). Available on: www.teriin.org/events/CoP15/Forests.pdf.

Angelsen, A., Brockhaus, M., Kanninen, M., Sills, E., Sunderlin, W. D. and Wertz-Kanounnikoff, S., 2009, *Realising* REDD+: national strategy and policy options. *CIFOR, Bogor, Indonesia*. Available on: http://www.cifor.org/publications/pdf_files/Books/BAngelsen0902.pdf.

Araya, Y. H., 2009, Urban land use Change Analysis and Modeling: A Case Study of Setubal and Sesimbra, Portugal. Master thesis, Institute for Geoinformatics, University of Munster, Munster, Germany.

Barik, S. K. and Darlong, V. T., 2007, Natural Resources Management Policy Environment in Meghalaya Impacting Livelihood of Forest Poor. Centre for International Forestry Research (CIFOR), BOGOR, Indonesia, 1-55.

Chatterjee, S., Saikia, A., Dutta, P., Ghosh, D., Pangging, G. and Goswami, A. K., 2006, Biodiversity significance of north-east India. Background paper No. 13, WWF-India. Available on: mdoner.gov.in/writereaddata/ ./13Biodiversity9583338441.pdf.

Clark Labs, 2010, *Modeling REDD baselines using IDRISI's Land Change Modeler*. IDRISI Focus paper, Clark University, Worcester. Available on:www.clarklabs.org/applications/upload- /idrisi_focus_paper_redd.pdf.

Cramér, H., 1999, Mathematical methods of statistics. Princeton University Press, Princeton.

Datta-Roy, A., Ved, N. and Williams, A. C., 2009, Participatory Elephant Monitoring in South Garo Hills: Efficacy and Utility in a Human-Animal Conflict Scenario. *Tropical Ecology*, 50, 163-171

Eastman, J. R., 2009, IDRISI Taiga, guide to GIS and remote processing. Clark University, Worcester, 234-256

FSI, 2011, India state of forest report 2011. Forest Survey of India, Ministry of Environment and Forests, Government of India, Dehradun, 181-185

Gautam, R. K. and Panigrahi, S., 2007, Leaf Nitrogen Determination of Corn Plant using Aerial Images and Artificial Neural Networks. *Canadian Biosystems Engineering*, 49, 7.1-7.9

Giriraj, A., Irfan-Ullah, M., Murthy, M. S. R., and Beierkuhnlein, C., 2008, Modelling Spatial and Temporal Forest Cover Change Patterns (1973-2020): A Case Study from South Western Ghats (India). *Sensors*, 8, 6132-6151.

Gorte, R. W., 2007, Carbon sequestration in forests. CRS Report for Congress, Order Code: RL31432. Available on: www.fas.org/sgp/crs/misc/RL31432.pdf.

Government of Meghalaya, 2005, State of the Environment Report, Meghalaya, Department of Environment and Forests, Government of Meghalaya, Shillong.

Gullison, R. E., Frumhoff, P. C., Canadell, J. G., Field, C. B., Nepstad, D. C., Hayhoel, K., Avissar, R., Curran, L. M., Friedlingstein, P., Jones, C. D. and Nobre, C., 2007, Tropical Forests and Climate Policy. *Science*, 316, 985-986

IPCC, 2007, Climate change 2007: the physical science basis: summary for policymakers. Available on: http://www.ipcc.ch/wg1 spm 17apr07.pdf.

Kaimowitz, D., 2008, The Prospects for Reduced Emissions from Deforestation and Degradation (REDD) in Mesoamerica. *International Forestry Review*, 10, 485-495

Kumar, A., Marcot, B. G. and Saxena, A., 2006a, Tree Species Diversity and Distribution Patterns in Tropical Forests of Garo Hills. *Current Science*, 91, 1370-1381.

Kumar, A., Marcot, B. G., and Roy, P. S., 2006b, Spatial Patterns and Processes for Shifting Cultivation Landscape in Garo Hills, India. In Patterns and processes in forest landscapes – consequences of human management, edited by R. Lafortezza, and G. Sanesi *Proceedings of the 4th meeting of IUFRO Working Party* 8.01.03, Sept 26-29, Locorotondo, Bari, Italy, 63-70.

Kumar, A., Marcot, B. G. and Talukdar, G., 2010, Designing a Protected Area Network for Conservation Planning in jhum Landscapes of Garo Hills, Meghalaya. *Journal of Indian Society of Remote Sensing*, 38, 501-512.

Marcot, B. G., Kumar, A., Roy, P. S., Sawarkar, V. B., Gupta, A. and Sangma, S. N., 2002, Towards a Landscape Conservation Strategy: Analysis of jhum Landscape and Proposed Corridors for Managing Elephants in South Garo Hills District and Nokrek area, Meghalaya. *Indian Forester*, February, 207-216

Menon, S. and Bawa, K. S., 1997, Applications of Geographic Information Systems, Remote Sensing, and a Landscape Ecology Approach to Biodiversity Conservation in the Western Ghats. *Current Science*, 73, 134-145

Miller, A. B., Bryant, E. S., and Birnie, R. W., 1998, An Analysis of Land Cover Changes in the Northern Forest of New England using Multi-

Temporal Landsat MSS data. *International Journal of Remote Sensing*, 19, 245-265.

Ministry of Tourism, 2003, *20 Years Perspective Plan: Meghalaya*. Ministry of Tourism, Government of India, New Delhi.

Munsi, M., Areendran, G. and Joshi, P. K., 2012, Modeling Spatio-Temporal Change Patterns of Forest Cover: A Case Study from the Himalayan Foothills (India). *Reg Environ Change* doi: 10.1007/s10113-011-0272-3.

Olander, L. P., Gibbs, H. K., Steininger, M., Swenson, J. J., and Murray, B. C., 2008, Reference Scenarios for Deforestation and Forest Degradation in Support of REDD: A Review of Data and Methods. *Environmental Research Letters*, 3, doi: 10.1088/1748-9326/3/2/025011.

Puyravaud, J., 2003, Standarizing the Calculation of the Annual Rate of Deforestation. *Forest Ecology and Management*, 177, 593-596

Ravindranath, N. H., Srivastava, N., Murthy, I. K., Malaviya, S., Munsi, M., and Sharma, N., 2012, Deforestation and Forest Degradation in India – Implications for REDD+. *Current Science*, 102, 1117-1125

Samrakshan Trust, *Nature tour to the "land of perpetual winds" South Garo Hills, Meghalaya, India*. Available on: www.samrakshan.org/Eco.../Eco%20Tourism-%20Brochure.pdf.

Tavoni, M., Sohngen, B. and Bosetti, V., 2007, Forestry and the Carbon Market Response to Stabilize Climate. FEEM Working Paper No. 15.

Tiwari, S. K., Karyong, S. S., Sarkar, P., Choudhury, A. and Williams, A. C., 2005, Elephant Corridors in North-Eastern India. In *Right of Passage: Elephant corridors of India*, edited by V. Menon, S.K. Tiwari, P.S. Easa, R. Sukumar. Conservation Reference Series No. 3, Wildlife Trust of India, New Delhi, 154-205

UN-REDD Programme, *About REDD+*. Available on:http://www.unredd.org/AboutREDD/tabid/582/-Default.aspx