Multi-Scale Forest Biomass Assessment and Monitoring in the Hindu Kush Himalayan Region: A Geospatial Perspective

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About ICIMOD

The International Centre for Integrated Mountain Development, ICIMOD, is a regional knowledge development and learning centre serving the eight regional member countries of the Hindu Kush Himalayas – Afghanistan, Bangladesh, Bhutan, China, India, Myanmar, Nepal, and Pakistan – and based in Kathmandu, Nepal. Globalization and climate change have an increasing influence on the stability of fragile mountain ecosystems and the livelihoods of mountain people. ICIMOD aims to assist mountain people to understand these changes, adapt to them, and make the most of new opportunities, while addressing upstream-downstream issues. We support regional transboundary programmes through partnership with regional partner institutions, facilitate the exchange of experience, and serve as a regional knowledge hub. We strengthen networking among regional and global centres of excellence. Overall, we are working to develop an economically and environmentally sound mountain ecosystem to improve the living standards of mountain populations and to sustain vital ecosystem services for the billions of people living downstream – now, and for the future.

Special Publication

Multi-Scale Forest Biomass Assessment and Monitoring in the Hindu Kush Himalayan Region: A Geospatial Perspective

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About This Volume

Forest biomass monitoring is becoming increasingly relevant in the context of sustainable livelihoods and REDD+ monitoring, verification, and reporting (MRV), and there is a growing need to develop more standardized methodologies. The governments of the Hindu Kush Himalayan region have been active in this area through various initiatives and projects for the past decade.

In December 2013, the International Centre for Integrated Mountain Development (ICIMOD), in collaboration with the International Society for Photogrammetry and Remote Sensing (ISPRS), held an international expert meeting on 'Geospatial Information Systems for Multi-scale Forest Biomass Assessment and Monitoring in the Hindu Kush Himalayan Region' in Kathmandu, Nepal. Papers were presented on various aspects of forest biomass monitoring in the different countries of the region, as well as the international state-of-the-art. The participants appreciated the opportunity for exchange and mutual learning with others from the region and expressed a strong interest in continuing collaborative research in this area. The scientific contributions were distributed during the meeting in the form of a 'Draft Proceedings'. As interest in this topic is growing worldwide, and with encouraging advances in this field in the Hindu Kush Himalayan region, ICIMOD decided to publish the papers in the form of this Special Publication to disseminate the findings to a wider audience. The book provides a comprehensive overview of forest biomass monitoring activities in the Hindu Kush Himalayan region and highlights the different capacities that exist. The papers have undergone external review by international experts in the field of remote sensing and forest biomass monitoring, as well as editing and professional layout.

Acronyms and Abbreviations

AGB	above ground biomass
ALS	airborne laser scanning
BA	basal area
BEF	biomass expansion factor
CDM	Clean Development Mechanism
CPA	crown projected area
DBH	diameter at breast height
FAO	Food and Agriculture Organization of the United Nations
FBD	Fine Beam Dual acquisition mode (PALSAR)
FBS	Fine Beam Single acquisition mode (PALSAR)
FCPF	Forest Carbon Partnership Facility
FOTO	Fourier Textural Ordination Method
FSI	Forest Survey of India
FSMP	Forestry Sector Master Plan
GHG	greenhouse gas
GIS	geographic information system
GPS	global positioning system
HH	horizontal-horizontal
HKH	Hindu Kush Himalayas
HSR	high spatial resolution
HV	horizontal-vertical
IPCC	Intergovernmental Panel on Climate Change
JAXA	Japan Aerospace Exploration Agency
LAI	leaf area index
LAMP	Lidar-Assisted Multi-Source Program
Lidar	Light Detection and Ranging
masl	metres above sea level
MODIS	Moderate-Resolution Imaging Spectroradiometer
MRV	monitoring, reporting, and verification
NDVI	Normalized Difference Vegetation Index
NFI	National Forest Inventory (India)
OBIA	object based image analysis
OIGF	Office of the Inspector General of Forests (Pakistan)
PALSAR	Phased Array L-band Synthetic Aperture Radar
PCA	principal component analysis
PFI	Pakistan Forest Institute
PLR	PALSAR polarimetric acquisition mode
REDD+	Reducing Emissions from Deforestation and Forest Degradation
RMSE	root mean square error
SAR	Synthetic Aperture Radar
SOC	soil organic carbon
TM	Thematic Mapper
UNFCCC	United Nations Framework Convention on Climate Change
VHR	very high resolution
VHSR	very high spatial resolution
VV	vertical-vertical

Foreword

Forest covers a large part of the Hindu Kush Himalayan (HKH) region and plays a vital role in confronting the challenges of climate change and improving livelihoods for the growing population. The HKH region has seen very high levels of deforestation and forest degradation over recent decades. Conversion from forest to other land uses often results in a substantial loss of carbon from the biomass pool, and changes in forest cover due to deforestation, growth dynamics, and natural disturbance may affect the role and function of the forest ecosystems.

Reducing Emissions from Deforestation and Forest Degradation (REDD), and the expanded form REDD+, are global policies under the United Nations Framework Convention on Climate Change (UNFCCC). These policies reward the forestry and land-use sector through an incentive mechanism with the aim of reducing the concentration of carbon dioxide in the atmosphere. Payments are made for conserving forest carbon stocks, and maintaining and increasing forest cover. Monitoring systems that allow for credible measurement, reporting, and verification (MRV) of activities are among the most critical elements for the successful implementation of REDD+. Monitoring of forest carbon emissions is essential in order for compensation to be paid for emissions avoidance or reduction through conservation, and requires both remote sensing and ground-based data.

Monitoring of forest carbon and assessment of biomass has become very important in the Hindu Kush Himalayan region, where it is hoped that the REDD+ mechanism will prove useful in addressing the ongoing problems of deforestation and degradation. It is especially important in this very large and poorly accessible region to explore the use, and evaluate the effectiveness, accuracy, and cost, of different remote sensing techniques at different scales. I am pleased to present this Special Publication, which provides an excellent overview of the status of forest biomass monitoring systems in the countries of the HKH region, and highlights results, challenges, and opportunities in the application of active and optical sensors for biomass assessment. The regional country contributions are complemented by papers from international experts that describe the technological potential of cutting-edge remote sensing techniques. The overview of the current status of biomass estimation and applicability of certain techniques and methods also enables us to reflect on a way forward towards more standardized biomass monitoring and REDD+ MRV systems at different scales in the region.

ICIMOD has developed periodic forest cover mapping initiatives and identified forest change prone areas that are in critical need of forest management. Pilot studies have also been conducted in Nepal on the estimation of biomass using satellite techniques. Exciting scientific advances are to be expected in the future, with satellite techniques becoming more mainstream and affordable, while newly available sensors will increase the potential for effective and consistent forest biomass monitoring.

ICIMOD is pleased to play a key role in convening stakeholders of its member countries and facilitating discussions regarding standard methods for forest biomass assessment. ICIMOD is well positioned to coordinate capacity building efforts due to its regional focus and broad expertise in forestry and geospatial applications in the context of REDD+. I would like to thank USAID and NASA for their support under the SERVIR-Himalaya initiative, which has made this Special Publication possible.

David Molden, PhD
Director General, ICIMOD

Foreword

The Hindu Kush Himalayan (HKH) region is characterized by enormous diversity in its forests and other flora, its fauna, and its indigenous peoples. There is also a great diversity in the infrastructure available to measure the status and changes in forests in the different countries. Much of this diversity comes from the topographic complexity of the region. The topography creates an enormous challenge, but a challenge that countries must meet if they are to have a proper understanding of what is happening in their forests and if they are to benefit from the opportunities arising from REDD+ and related initiatives. Measuring biomass and its changes is fundamental to meeting this challenge.

The meeting at ICIMOD on 9–10 December 2013 from which this publication springs represented both a desire to share experience and knowledge on biomass measurement among the HKH countries and a look forward at how new (and old) technologies can help to address the issue. These are exciting times for using space-based technology to measure biomass, as a suite of new missions will come on stream over the next few years: the ESA BIOMASS P-band radar mission; the recently approved NASA Global Ecosystem Dynamic Investigation (GEDI), which will be a vegetation Lidar deployed on the International Space Station; the NASA L-band NISAR mission to measure forest disturbance and recovery; and systematic L-band SAR measurements of the world's forests by JAXA's ALOS-2 mission and the Argentinean SAOCOM pair of satellites.

However, although these missions offer great opportunities, their contributions need to be understood within the context of the needs, knowledge, and developing infrastructure of the HKH countries. Furthermore, extracting information from these missions reliably requires close working relationships with organizations that can help to train and validate their measurements. This is particularly true in the HKH region, where steep terrain and the resultant significant variations in forest properties will create problems for accurate inversion of the satellite data.

The HKH community can contribute greatly to this joint effort in many ways: by providing a focus for efforts to understand and correct terrain effects; by obliging satellite mission scientists to understand the value of their data within the context of HKH national needs, and the implications for data quality and access; by making in situ and airborne data available for training and calibration; by evaluating the quality of the satellite data products; and by investigating whether these data significantly improve their monitoring, reporting, and verification systems. Thus, the papers presented here provide not end-points but signposts aiding the development of the international collaboration needed to make the most of the opportunities of the coming decade.

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Executive Summary

There is a growing need for consistent forest biomass monitoring in the context of sustainable livelihoods, ecosystem services, and REDD+ monitoring, reporting, and verification (MRV). Reliable baseline data on forest biomass need to be developed for proper reference. It is imperative to establish standardized methods at multiple scales which can be easily replicated. This publication presents a review of current biomass assessment and monitoring systems and the application of geospatial data and tools in the Hindu Kush Himalayan (HKH) region, and the scope for strengthening such systems. Section 1, with seven papers, gives an overview of the geospatial datasets, models, and methodological frameworks being adopted in different countries in the region, and indicates the different capabilities related to biomass assessment and geospatial analysis and the different levels of preparedness and implementing capacity for REDD+ MRV.

The papers in Sections 2 and 3 (five in each section) describe a number of examples of applications of active and optical sensors using a range of models, methods, specific data, and techniques.

Among the active sensors described in Section 2, synthetic aperture radar (SAR) systems show particular promise as a result of their cloud penetrating qualities and applicability to forest/non-forest mapping, monitoring of deforestation, and forest biomass mapping. Laser imaging detection and ranging (Lidar) is also a promising active sensor. Encouraging results are reported for applications of Lidar data in combination with very high resolution (VHR) optical satellite data, and for applications of the Lidar Assisted Multi-source Program (LAMP) – a forest inventory methodology that integrates Lidar data, field data, and moderate resolution satellite data to estimate forest biomass over large areas. Studies in Bangladesh and Pakistan elaborate on the opportunities and limitations of using active sensors.

The studies on optical sensors in Section 3 also present a number of interesting results. There is general agreement that integration of (optical) remote sensing data with field inventory data can form part of a useful approach to obtaining improved forest above ground biomass (AGB) estimates. The 'FOTO' method (Fourier-based textural ordination) applied in one of the studies focuses on texture analysis of (very) high resolution imagery, and provides meaningful information on vegetation properties and biomass. Promising results are also reported in a study using very high and medium resolution satellite optical datasets; a crown projected area (CPA) vs. basal area (BA) model was developed and validated at the watershed level using only limited field data.

Key Messages

- Forest biomass baseline assessment and monitoring at multiple scales is needed for management of sustainable forests to support livelihoods and to gain carbon mitigation benefits through mechanisms like Reducing Emissions from Deforestation and Forest Degradation (REDD+).

- The main challenges in current forest carbon estimation are related to the prohibitive costs of extensive field measurements, limited use of optimal field sampling designs, development of spatially consistent estimations, and controlling uncertainty due to errors from allometry and sampling design.

- Open source remote sensing data and tools related to forest biomass assessment hold part of the key to addressing these challenges at different scales.

- There is a critical need to formulate and implement a consistent and standardized methodological framework for forest biomass baseline assessment and monitoring at multiple scales using ground- and space-based protocols.

- A proper inventory of existing expertise related to remote sensing based forest biomass monitoring in the countries of the Hindu Kush Himalayan region will help in outlining an effective capacity building strategy to ensure that adequate capacity is in place.

- Cross learning opportunities will facilitate the implementation of standardized approaches and techniques.

- International collaboration could foster further standardization of methods and bring in new satellite missions on biomass assessment and monitoring.

- ICIMOD, with its regional focus, could play a key role in convening stakeholders in its member countries to facilitate agreements related to standard methods for forest biomass assessment and coordinate capacity building efforts.
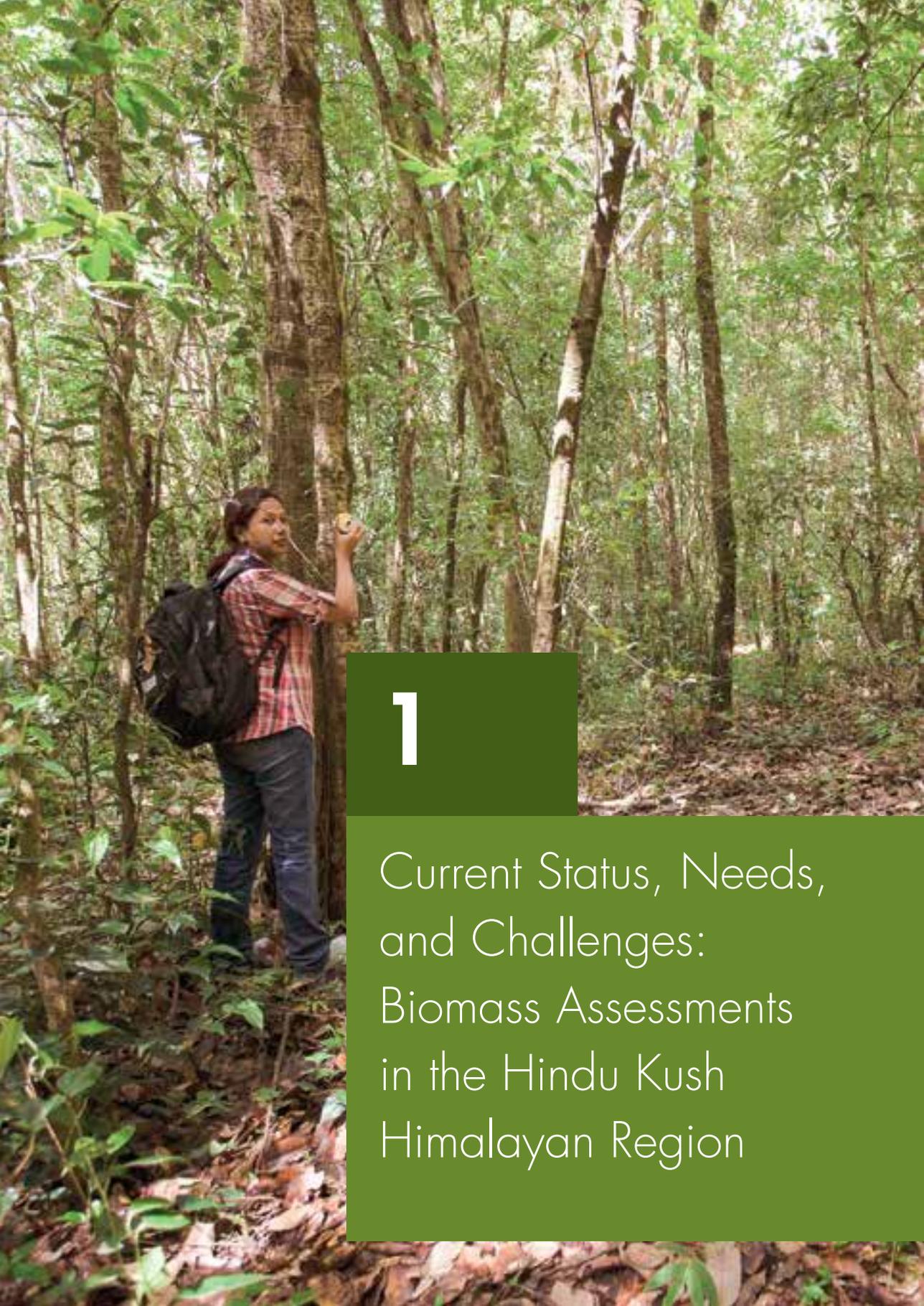
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Current Status, Needs, and Challenges: Biomass Assessments in the Hindu Kush Himalayan Region

Multi-Scale Forest Biomass Assessment of the Hindu Kush Himalayan Region

Scope and Challenges of Geospatial Applications

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*F*orest resource conservation through community-based programmes has become an integral part of forest management in the Hindu Kush Himalayan (HKH) region. Reliable baseline assessment and monitoring strategies at multiple scales are needed to generate optimal supply–demand resource scenarios for effective use of forest resources and to leverage carbon mitigation benefits through mechanisms like the Clean Development Mechanism (CDM) and Reducing Emissions from Deforestation and Forest Degradation (REDD). There is a critical need for forest biomass assessment and monitoring at multiple scales using ground and space-based protocols. However, the use of geospatial information systems is still at an early stage due to the lack of a uniform and consistent methodological framework and varying capacity of countries in the HKH region. This paper describes the available geospatial datasets and models relevant for the region; the current status of assessment levels and needs at HKH regional, national, and local levels; and areas of research to strengthen geospatial applications for multi-scale biomass assessment.

Keywords: Hindu Kush Himalayas (HKH), REDD+, multiple scales, and geospatial applications

Introduction

In the debate on greenhouse gas (GHG) emissions as the prime cause for the perceptible global warming, forest carbon flux assessment has gained the attention of researchers and practitioners alike. The roles played by terrestrial ecosystems in the global carbon (C) cycle, and especially the role of intact forests as a carbon sink, and of deforestation and forest degradation as a GHG source, have been widely recognized as crucial since the 13th session of the Conference of the Parties (COP 13) to the United Nations Framework Convention on Climate Change (UNFCCC) in Bali in 2007, and publication of the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) in the same year (IPCC 2007). This is mainly due to the early estimations that deforestation and degradation of forest ecosystems contributes up to one-fifth of the world's total anthropogenic GHG emissions. Carbon sequestration was also reported to be a potentially effective mitigation method to counter

global warming at a lower cost than that of the massive energy conservation and innovation adjustments needed to reduce the use of fuel in high-energy world economies.

Forests play an important role in the global carbon cycle, and both influence and are influenced by climate change. Forest ecosystems contain more than half of all terrestrial carbon and account for about 80% of the exchange of carbon between terrestrial ecosystems and the atmosphere (FAO 2010). At the same time, 14 million hectares of global forest cover is lost annually (FAO 2010). The future global trend of pressure on the remnant forest cover can be gauged from the fact that five billion new middle class consumers are expected by 2030 (Cotula 2011). This will mean a marked increase in the demand for energy, food, material, and consumables that is driving forest conversion, and especially in the five commodities considered to be closely linked with widespread deforestation: palm oil, soy, beef, leather, timber, and biofuels.

In the Hindu Kush Himalayan (HKH) region, the system of agriculture, forest, and other land use (AFOLU) constitutes an important component of livelihoods and means of support for creating and safeguarding more climate-resilient livelihoods. AFOLU-based systems support around 70% of fuel and fodder demand in the region, and their CO_2 mitigation potential is also thought to be significantly high. However the current low investment and lack of innovation to improve the productive interface between forest-dependent people and sustainable forest ecosystem services do not augur well for addressing climate change. There are currently four key opportunities for renewing the role of forests as an effective and efficient carbon sink:

- **Putting a price on ecosystem services.** Economic valuation of all forest products and services
- **Incentivizing for carbon sink services.** Creating innovative financing mechanisms and markets for carbon sink services
- **Encouraging investment in sustainable forest management.** Proactive management to sustain forest ecosystem goods and services.
- **Strengthening governance.** Improving forest governance

Validated research on carbon flux potential and measurement is needed as a basis for achieving these opportunities for forest carbon management; tracking and monetizing carbon sinks using simple carbon flux monitoring methodologies is essential. The extent of deforestation and degradation is considered to be a primary measure for carbon mitigation strategies and there is a critical need for assessment and monitoring of forest extent and biomass at multiple scales using ground and space-based protocols. Satellite-based monitoring of deforestation is largely proven technically, but the establishment and application of operational forest cover monitoring systems has a long way to go in most of the HKH countries. The use of geospatial information systems remains at an early stage due to the lack of a uniform and consistent methodological framework and varying capacity within different countries. At present, degradation assessments and monitoring focusing on forest biomass are generally performed through community- and state-owned ground-level monitoring systems.

The diverse forestry initiatives in the region require methodologies and approaches to bring value addition to geospatial systems (remote sensing and in-situ measurements) in order to meet biomass assessment and mitigation compliance procedures, and to support uncertainty control and seamless scaling up and integration into sub-national and national frameworks. This paper describes the available geospatial datasets and models relevant for the region; the current status of assessment levels and needs at HKH regional, national, and local levels; and areas of research to strengthen geospatial applications for multi-scale biomass assessment.

Forest Sampling and Biomass Estimation: Data Requirements and Models

The precise estimation of forest biomass depends on efficiency at three stages of the quantification process: design, estimation, and inference. The design stage means selecting the design for data gathering; the estimation stage involves selecting and using estimators for the parameters of interest, i.e., population means and totals; and the inference stage analyses the accuracy of these estimators, i.e., calculation of standard errors and confidence levels. In natural forested ecosystems, selected features are typically identified by their location. Thus forest biomass sampling needs a spatial perspective: sampling in space. There are two scientifically based approaches for sampling and extrapolating from a sample to an entire population: design methods and model-based methods. The principle difference between them lies in the source they use for randomness.

Design-based estimation: Geospatial data and methods

In classical design-based sampling theory, the source of randomness is the probability introduced by the sampling design to the various subsets of a population. Inference rests on the stochastic structure introduced by the sample selection. Hence one of the important ways of enhancing the efficiency of design is to develop a reliable stratification of a complex population and optimally sample subpopulations. Satellite remote sensing provides precise stratification in terms of forest crown density, forest types, communities, and species formations which can form the basis for reducing the strata variance and making precise estimates. This becomes more relevant in the context of the high degree of variability in spatial distribution of vegetation types across the HKH region. Spatial explicitness in the estimates can be brought out at the desired scale and accuracy using a geographical information system (GIS) by accounting for the strata proportions and value of the category of interest per unit area for a given strata. However, the resolution of spatial explicitness depends on the details of stratification and intensity of ground sampling.

Different forest types vary significantly in terms of the ratio of below and above ground biomass, annual increment, and biomass density, which determine the standing biomass levels. Kaul et al. (2010) have described how forest type information was used in different studies related to the assessment of forest carbon pools in India. Precise delineation of the boundaries of the groups of different types, single species formations, and mixed species formations, offer

a unique opportunity for developing spatially balanced sampling designs, improving the precision of the field sampling, and attributing appropriate biomass expansion factors (BEF) at the national, state, or bioclimatic zone level to improve the precision of the estimates.

Spatially explicit forest type products suitable for use at HKH regional level are available as open-source databases from global land cover and vegetation products (Annex, Table A1), and spatially explicit forest type databases using satellite and ground-based information suitable for use in national and sub-national level biomass estimations exist for China and India (Annex). While significant information on forest composition exists from ground surveys in the other countries in the HKH region, there is a lack of spatially explicit forest type databases that can be used for forest biomass estimation and management.

The relationship between forest crown cover and biomass is strongly established and has been widely used at different scales. The forest crown density (percentage) is delineated using widely available medium resolution satellite data and used as a stratification input for ground inventory in estimations at national and sub-national levels. The different forest cover parameters available as open-source products and relevant for biomass estimation at different scales are presented in the Annex (Table A1). The crown projected area (CPA) delineated using very high resolution satellite data has been found to provide reliable information on forest basal area and the number of trees at forest stand level. Several studies have been published using this technique across different parts of the HKH region at the research level; the approach needs to be integrated in regular operational sub-national and local level assessments. Several national and sub-national biomass inventories over different parts of the HKH region have been developed using design-based models with remote sensing data.

Model-based estimations: Geospatial data and methods

Forest structure and biomass often exhibit nonlinear variations across space and variable interactions across temporal and spatial scales. Hence, the traditional methods of uniform extrapolation of field-based sample biomass estimates over larger areas suffer from a large uncertainty. In addition, spatially explicit estimates can potentially provide good insights for carbon monitoring, leakage, additionality, and prediction of biomass over time, as a function of change due to land cover and land use. With the advent of availability of multi-resolution satellite data, powerful data mining, and self-learning algorithms, there has been a paradigm shift from simple area-based extrapolation methods to model-based extrapolation.

In the model-based approach, the inference rests entirely upon the validity of the model describing the real world. All the randomness in this inference is due to the population and not the sampling method, as in the design-based approach. Where the design-based approach requires independent selection of units, the model-based approach considers the independence of the sampling units, and thus spatial correlations between the sampling units need to be taken into account. Even when models are used in the design-based approach, the validity of inference is ensured by the sampling design and not by the validity of the model.

In this context, remote sensing based spatial information, geostatistical tools, and non-parametric tools provide an effective means to develop robust models. Remotely sensed reflectance data based on the physiognomy, composition, and phenology of vegetation are used as a proxy to estimate the biomass. The reflectance regulated by physiognomy and composition is understood using high resolution satellite data, and the phenology is quantified using high temporal resolution and medium spatial resolution satellite data. The model-based approaches relate the spatial variability of forest spectral reflectance across each unit (pixel) of the remotely sensed image with field-based biomass, and develop a model that associates the biomass value for each pixel. This results in development of spatially explicit biomass as a function of the resolution of the satellite data used, hence the model can be developed from local to regional and national scales. As a result of these advantages, estimation of forest volume and biomass using satellite reflectance-based models has recently been drawing attention.

Qingxi and Feng (2003) used a multi-regression equation and neural network model to estimate the forest biomass on the southern side of the Xiaoxing'an Mountains. The model was established using TM imagery, together with 232 plots of forest inventory data, including environmental and biological factors, to develop the regression equation. Using forest inventory data for three inventory periods (1984–1988, 1989–1993, and 1994–1998) and synchronous NDVI (Normalized Difference Vegetation Index) data, Piao et al. (2005) developed a satellite-based approach for estimating China's total forest biomass carbon stocks. Karna et al. (2015) developed a high resolution, species-specific crown projected area and diameter model to estimate forest carbon over mid-Himalayan tracts of Nepal. Several such models have also been presented in different articles in this publication. These techniques have an enormous potential to use multi-resolution data and develop multiphase sampling approaches to integrate local measurements at national scales.

Forest allometry

Information is needed on volume equations, biomass expansion factors, and specific gravity of wood for estimation of above and below ground biomass, assessing the commercial and non-commercial parts of biomass, and other calculations. Biomass expansion factors are used to convert stand volume to above ground biomass and account for non-commercial components such as branches, twigs, bark, stumps, and foliage. The IPCC, FAO, Forest Survey of India (FSI), and Forest Research Institute of India have been publishing extensive information on these parameters in the form of reports. As part of the National Carbon Project of India under the ISRO-GBP programme, an effort was made to develop a database with specific volume equations and general equations for 753 regional species based on Forest Research Institute and FSI publications. Specific gravity data have been collected for 16,400 species in Asia. The specific gravity of 86 fuelwood trees and shrubs growing on wasteland and degraded sites has been added. In Nepal, allometric equations are mainly available for community forests with low diameter at breast height (DBH); these equations can produce errors in biomass and carbon estimation for bigger trees.

Multi-scale Assessment Systems

HKH regional level assessment

One of the critical challenges in the transboundary HKH mountain system is managing carbon sequestration and biodiversity within and among geographic regions, and estimating the effects of 'natural' disturbances on carbon storage and flux. Scaling of biogeochemical processes to regions, continents, and the world is also critical for understanding feedback between the biosphere and atmosphere in the analysis of global change. It is necessary to have this type of understanding on the interplay between forest ecosystem structure and function at the HKH regional scale, considering the high degree of latitudinal and altitudinal control of climate over the region. Studies along these lines could provide scientific evidence on the patterns of biomass change and associated drivers to support transboundary management.

Some of the diverse geospatial datasets available on forest distribution and biomass levels developed using multi-sensor remote sensing data are listed in the Annex (Table A1). These datasets contribute to understanding of patterns and drivers of change at a regional scale. The spatial distribution patterns of forest carbon at different latitude and altitude and under different disturbance regimes over the HKH region are shown in Figures 1 and 2. The forest patches (high disturbance regime) were identified using landscape metrics at half degree resolution grid level. The carbon estimates were generated for the HKH region using the global carbon datasets from Kindermann et al. (2008) at 20 x 20 km resolution.

Figures 1 and 2 show that the variation in forest carbon is greater along the latitudinal gradient than along the elevation gradient. This indicates a possible role of forests in land surface climatology along the latitudinal gradient. The high variability of patch forest carbon (disturbed regime) at different elevations may be due to anthropogenic and environmental heterogeneity, the total carbon in patch forest is also very small compared to forest overall. Understanding of the role of disturbance regimes on carbon sequestration in relation to landscape gradients could provide useful information for transboundary management at the landscape level.

Figure 3 shows the relationship between species diversity and level of basal area in deciduous forests in India in 25 bioclimatic zones. The graph shows three distinct groupings: in Group A, basal area increases with species diversity; in Groups B and C, basal area also increases with species diversity but at different threshold levels. These distribution patterns indicate how dominant species, bioclimatic and local topographic factors, and disturbance regimes control growth and species diversity. Sal mixed ecosystems in the lower elevation regions of the Himalayas have a high basal area but low diversity, whereas the mixed forest deciduous systems have a low basal area but high diversity. The spatial delineation of such zones using remote sensing and ground based data would help in demarcating zones that are more or less resilient to disturbance and climate change impacts.

Figure 1: **Forest and patch forest area and carbon stocks at different latitudes in the HKH region**
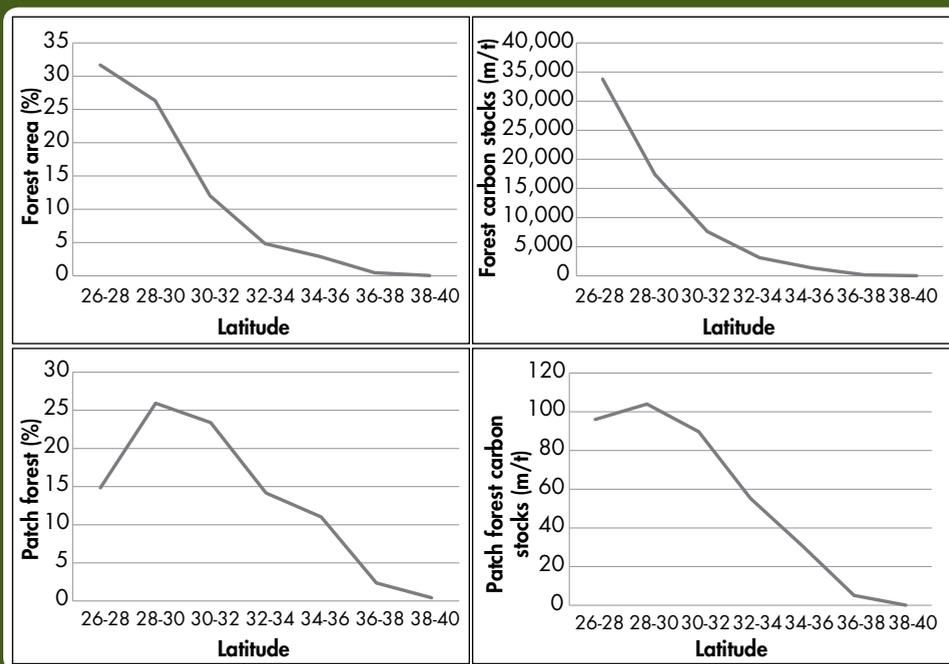
Figure 2: **Forest and patch forest area and carbon stocks at different elevations in the HKH region**
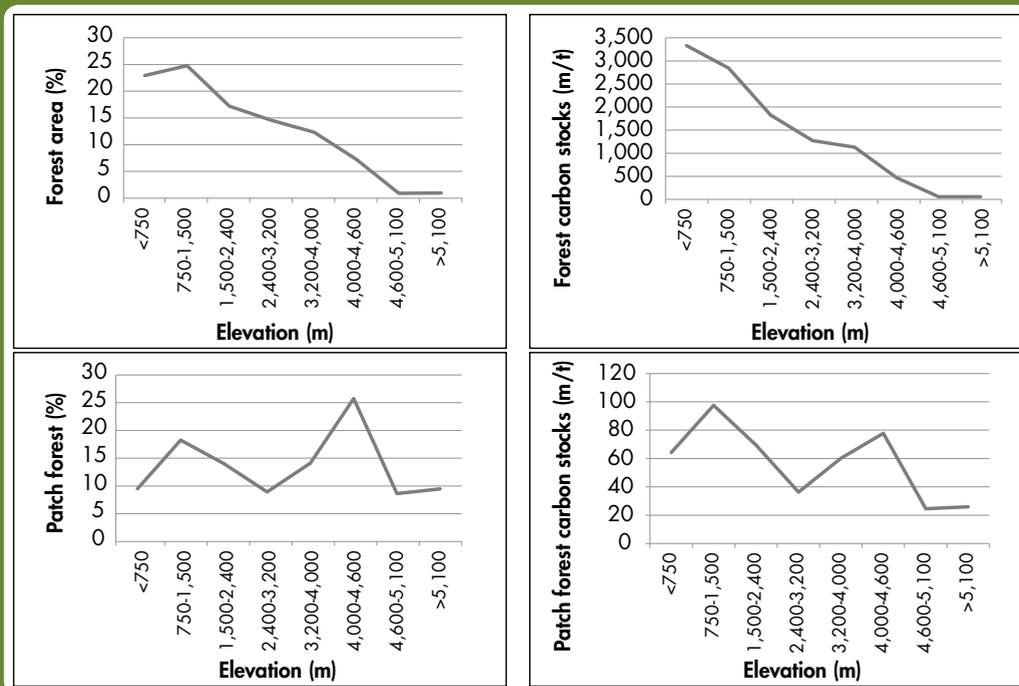
Figure 3: **Species diversity and basal area of deciduous forests in India**
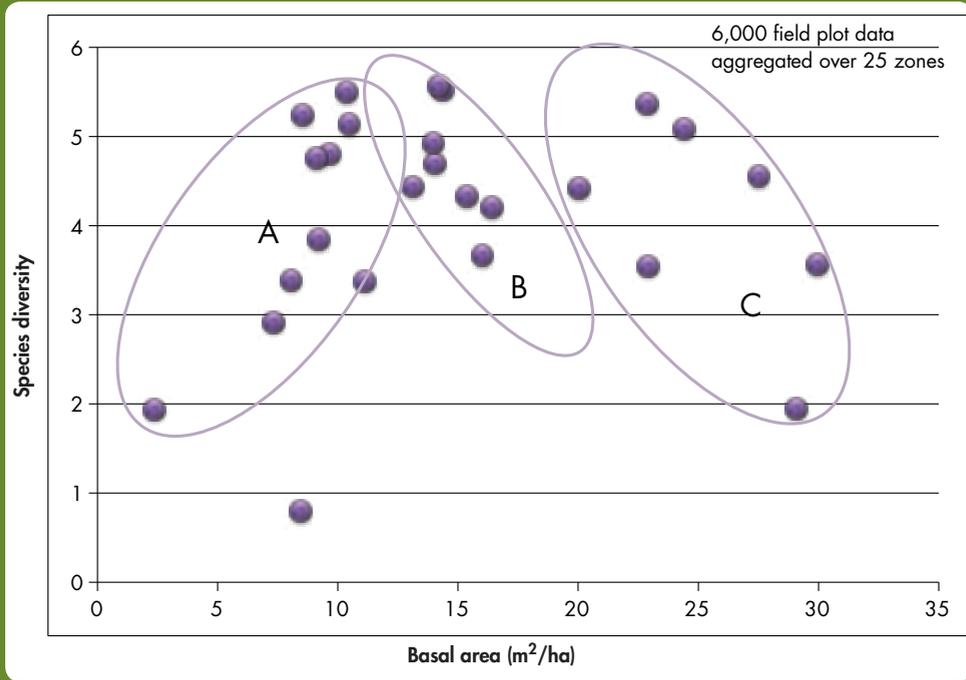
National and sub-national level biomass assessments

Currently, assessment of forest growing stock is done at national and sub-national levels. National growing stock estimates are developed using national-level multi-source forest inventories. In order to address sustainable forest management, the national forest inventories are made exhaustive in terms of parameters and data collected across the entire country. Most of the national inventories follow systematic sampling with fixed grids and proportional temporary and permanent sample points chosen for data collection.

In view of this complexity, national inventories involve intensive field sampling and are thus time and cost intensive. The estimates are generally planned over a five-year time interval. However due to time and cost constraints, biomass assessments in most HKH countries, apart from China and India, have not been carried out at regular intervals. Equally, national-level growing stock estimates over a large country do not provide realistic sub-national scenarios, while the next lower level assessments done at the district level are designed with district-specific requirements in terms of sampling design and time.

Low cost and rapid national and sub-national forest monitoring systems which can address deforestation and biomass changes are increasingly being developed. Such monitoring systems could provide consistent temporal databases that would enable estimation of

historical forest cover change, as well as an operational mechanism for monitoring forest at specified intervals on a regular basis. Such a coherent operational system would go a long way towards measuring and reporting changes in deforestation and/or forest degradation (biomass changes), in forest carbon conservation, and on carbon stock enhancement or reduction activities for GHG inventories and forest reference emission level estimates.

The contribution of geospatial approaches in developing low cost and rapid forest monitoring systems in the HKH region is immense. Forest cover monitoring is carried out operationally at regular intervals in China and India using remotely sensed satellite data. The International Centre for Integrated Mountain Development (ICIMOD) is developing harmonized time series forest cover databases and establishing operational systems for forest cover monitoring in association with the remaining countries under the NASA supported SERVIR-Himalaya initiative. However, efforts to develop monitoring systems for low forest biomass as a proxy for forest degradation still have a long way to go.

The studies carried out over China and India to develop satellite reflectance-based biomass models are also worth mentioning. Piao et al. (2005) developed a satellite-based approach for estimating China's forest total biomass carbon stocks using forest inventory data for three inventory periods, 1984–1988, 1989–1993, and 1994–1998, together with synchronous satellite based NDVI (Normalized Difference Vegetation Index) data. Region-specific spectral models are being developed across India as part of the ISRO National Carbon Project. The remote sensing models initially depend on more intensive ground data for model calibration and validation. The standardized models then provide spatially explicit biomass estimates based on reflectance data perceived as a function of change in land cover class and physical growth of forests.

These kinds of models have greater relevance where forest undergoes dynamic changes due to deforestation, reforestation, and afforestation under different anthropogenic interventions. Intensive ground data and high resolution satellite-based quantification of sites of dynamic change, followed by synoptic coarse scale assessment at a landscape scale and integration of the two scales of information to develop a national level framework for biomass assessment, could be explored as the basis for a cost and time effective national level monitoring system. Figure 4 shows a conceptual framework of this type which is being tested in Nepal.

Local scale assessments

Community forest management has been increasing in the HKH region as a process for sustainable management of forest resources. The success of community forest management lies in the fact that the local people receive tangible benefits from the conservation efforts they make. Tangible benefits are particularly clear from programmes like those under the Clean Development Mechanism and Reducing Emissions from Deforestation and Forest Degradation (REDD+). Effective monitoring of conservation efforts and their results has become a mainstay for payment mechanisms, and evolving REDD+ monitoring, reporting, and verification (MRV)

Figure 4: **Multi-scale national assessment framework**
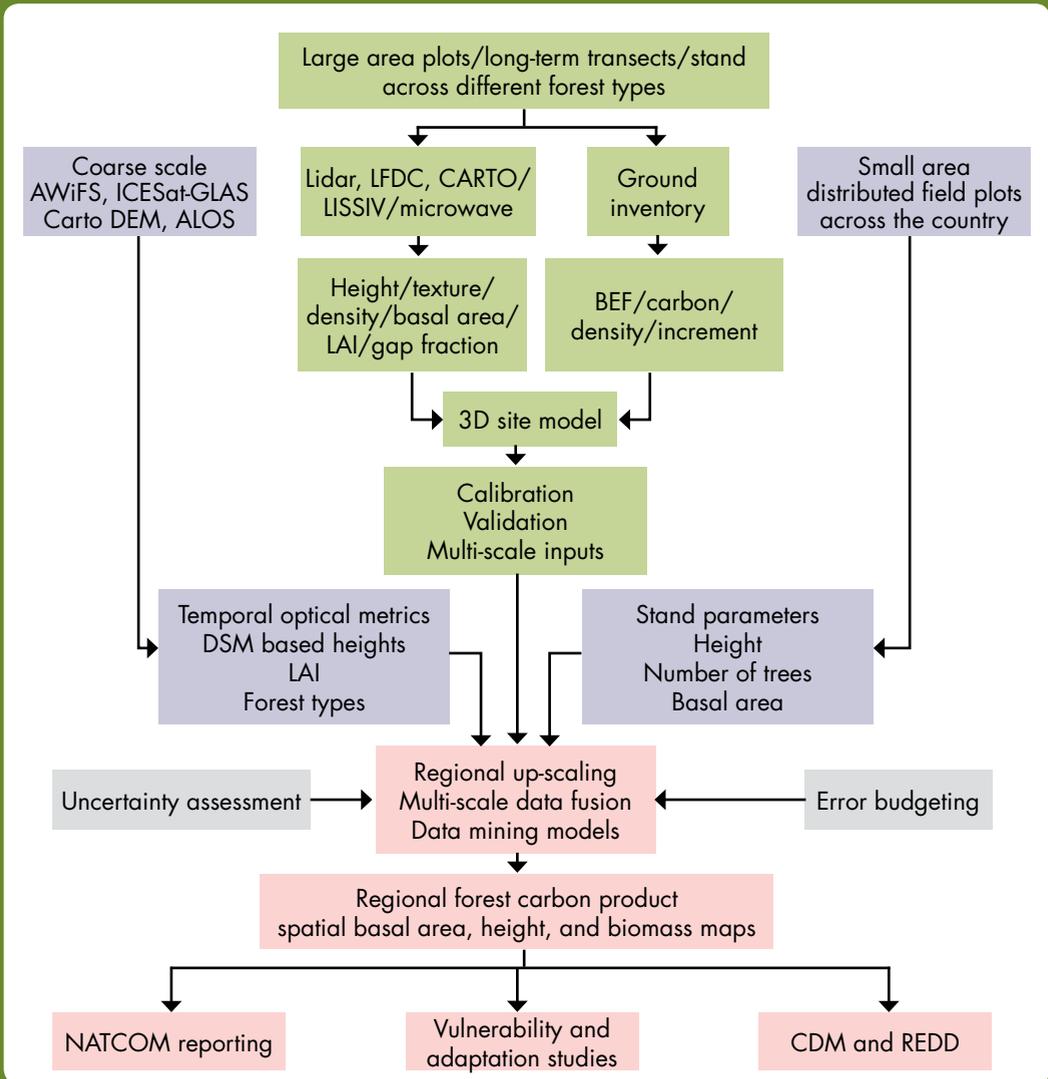
as a cost and time effective, locally implementable mechanism has become a challenge. The synergistic use of local ground measurements and adoption of low cost geospatial systems to develop synoptic scale of understanding offers a potentially viable system to be tested. In the following, we describe our experience of local scale monitoring of pilot REDD+ sites in Nepal.

Ground based participatory monitoring of REDD+ project sites

Since 2009, ICIMOD and partners Federation of Community Forestry Users Nepal (FECOFUN) and Asia Network for Sustainable Agriculture and Bioresources (ANSAB) have been implementing a pilot REDD+ project in collaboration with local communities in three

watersheds in Nepal covering more than 10,000 ha of forested area under community management. This pilot project, funded by the Norwegian Agency for Development Cooperation (Norad), looked at why and how a community can be involved in MRV.

The pilot project facilitated a sub-national level MRV system in which monitoring responsibilities were devolved to local communities through a participatory method with an opportunity to seek guidance and supervision from the district forest office (DFO). MRV is the single most important activity for performance-based forest management and determines the scale of payment and incentives. Community-based monitoring is a data source for MRV (Danielsen et al. 2011). The involvement of local communities in forest monitoring promotes a feeling of ownership, and motivates people to take on REDD+ responsibilities with performance-based forest management.

The project developed forest carbon stock measurement guidelines following IPCC 2006 Good Practice standards, and trained and supported community forest user groups to carry out forest measurements. Other authors have noted that local MRV may be cheaper than, and as accurate as, national-level alternatives (Puliti 2012) and that collecting data on their own forests engages local communities and reduces the costs of technology and experts (Dangi 2012). The communities in the project proved able to measure stock using standard forest inventory methods; mapping this methodology was tried, and shown to work, in several countries including India, Tanzania, Senegal, and Papua New Guinea. The communities carried out diameter measurement, boundary delineation, and species identification in permanent monitoring plots laid down at the project sites more effectively than outside professionals, and their involvement in monitoring activities also enhanced transparency (IGES 2012).

Low cost scientific tools: The potential of geospatial systems

The requirements in the REDD+ MRV process such as completeness, consistency, and correctness depend on spatial explicitness of the given observation or estimate from which they are developed. Plot-based low intensity ground monitoring has a limited scope to address certain critical components of community forest programmes such as additionality, leakage, and persistence, as such changes need to be evaluated at the landscape scale. Thus it is helpful to complement the limited permanent field plot-based carbon monitoring with more spatially explicit forest structure and biomass based monitoring using multi-resolution remotely sensing data.

Time series satellite data at 1 m resolution can provide information on detailed changes in crown size, number of crowns, crown overlap function, crown shadow, and crown gaps, and such satellite images are freely available through Google Earth and very low cost Indian satellite systems. Figure 5 shows some typical results for change in crown number over time. The monitoring of forest canopy morphology using such data could provide meaningful information on degradation or improvement of forest. CPA–basal area models using very high

Figure 5: **Change in tree crown size over time**
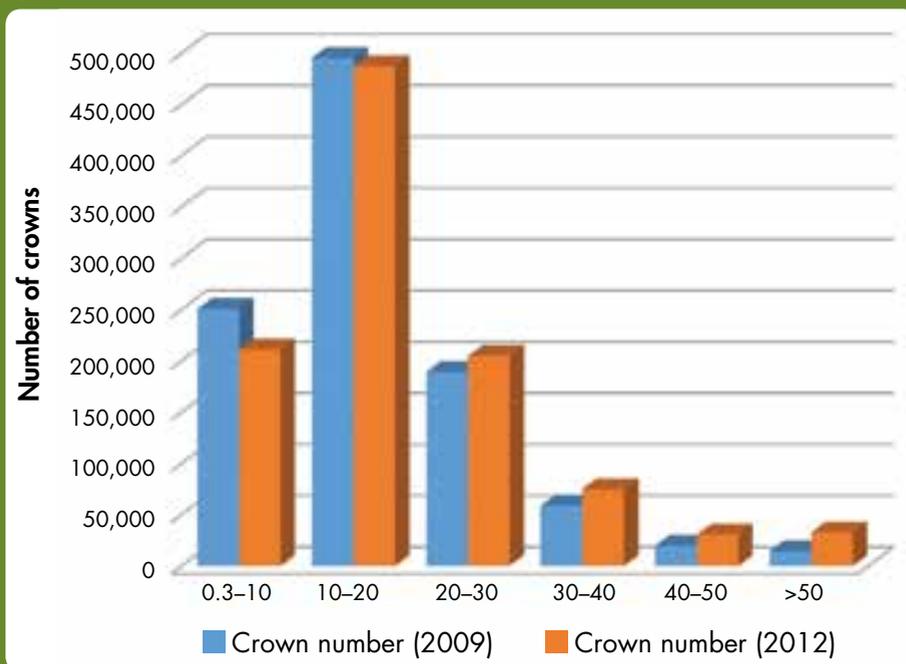
resolution data are also very useful for predicting basal area and biomass over an entire project site to quantify the dynamics of change even outside the permanent monitoring plots.

Pilot studies over selected sites have proven the usefulness and scientific feasibility of using geospatial data to provide a low cost monitoring system. The results are presented in another paper in this volume (Gilani et al. 2015). Efforts are being made to develop easily readable and understandable value-added geospatial products, and to carry out capacity building of local users in the use of such products in participatory forest monitoring.

Emerging Research Areas and Challenges

Enhanced forest biophysical data generation

The key challenges in regional and national level forest carbon estimation include optimizing field sampling, developing spatially consistent estimations, controlling uncertainty due to errors from allometry, sampling design, ensuring the quality of predictor and response variables, and using robust models for extrapolation. Remote sensing of forest biomass, which is directly correlated with carbon stored in forests, holds one of the keys to addressing these challenges at different scales. Since biomass is a three-dimensional metric, precise estimation requires biophysical measures addressing horizontal (e.g., canopy density/cover) and vertical (e.g., canopy height) structural characteristics of the vegetation. The availability of high

temporal large swath optical sensors like MODIS, SPOT, and AWiFS have enabled understanding of horizontal vegetation structure and the relationship with above ground biomass using parametric and non-parametric models. However, these models are constrained by the large volume of field inventory data required for training the model, and the availability of repeat measurements for time domain biomass assessments.

During the last decade, the scope for generating more biophysical information in the horizontal and vertical domains and estimating biomass has improved enormously due to the launch of very high resolution optical sensors, and airborne and space-borne microwave and Lidar systems. Very high spatial resolution optical systems have the potential to provide details on canopy morphology which can be related to biomass. Airborne microwave and Lidar systems have been used across the world to retrieve stand height and estimate biomass. Saatchi et al. (2011) prepared biomass carbon estimates over three tropical continents using tree height information based on GLASNOST and optical temporal metric information based on MODIS using data mining models. It is generally expected that measurement of above ground biomass (AGB) will become dominated over the next five years by methods that combine radar, Lidar, and optical data, which can provide spatial consistency in the estimates and optimize field inventories. The open-source satellite data currently available, their use, and comparative assessment in terms of cost, are summarized in the Annex (Tables A2, A3).

Uncertainty assessment and control

The uncertainties in assessing biomass and change can be grouped into three classes: spatial characterization, temporal characterization of forest cover and standing biomass, and use of precise ground-based forest allometric databases. Because of the high degree of spatial and temporal variability in rainfall, topography, and biotic disturbances, both forest type and standing biomass differ appreciably across space. Any national level estimate suffers at times from inaccuracy because of the inadequacy in accounting for spatial heterogeneity in terms of forest condition (crown density), forest type, and standing biomass. Uncertainty in important variables in the ground-based data such as biomass expansion factors, specific gravity of wood, annual increment, and wood extraction (fuelwood, thinning, logging, and others) also induce a large uncertainty in forest carbon stock assessment.

The challenges in carbon pools and flux estimates lie in the extent to which the degree of uncertainty can be reduced. The errors that can accumulate include: measurement errors at plot level; errors due to allometric relationships; sampling errors; and model prediction errors. Currently, carbon pool estimates rely on field measurements and are subject to measurement uncertainties. A shift towards multi-sensor remote sensing based biomass estimations with optimal field sampling is urgently needed. Remote sensing and ground-based Lidar systems help in intensive site characterization to develop models for biomass estimation and validation. These approaches would facilitate production of periodic biomass assessments using satellite data and limited ground information and reduce uncertainty. With the advent of the availability of geospatial tools and digital databases, spatially balanced field sampling designs could be

evolved using multiple layers of information to reduce errors in sampling. Currently, design-based models are used to develop regional and national estimates. Spatially disaggregated model-based estimation methods would help in optimizing errors during scaling up.

Conclusion

The use of diverse open-source data and tools in the HKH region for multi-scale biomass monitoring needs to be strengthened both in scientific terms and in improved capacity building. Development of scientific understanding on the relationship of forest biomass to different ecosystem processes at a regional level using consistent geospatial datasets will help support transboundary management. The increasing integration of community-based field biomass monitoring systems into national monitoring systems through a geospatial framework for scaling up will facilitate the optimization of national level reference emission level inventories. Value-added remote sensing products that can be understood by local level stakeholders will help to reduce the transaction costs involved in the REDD+ MRV mechanism.

Acknowledgements

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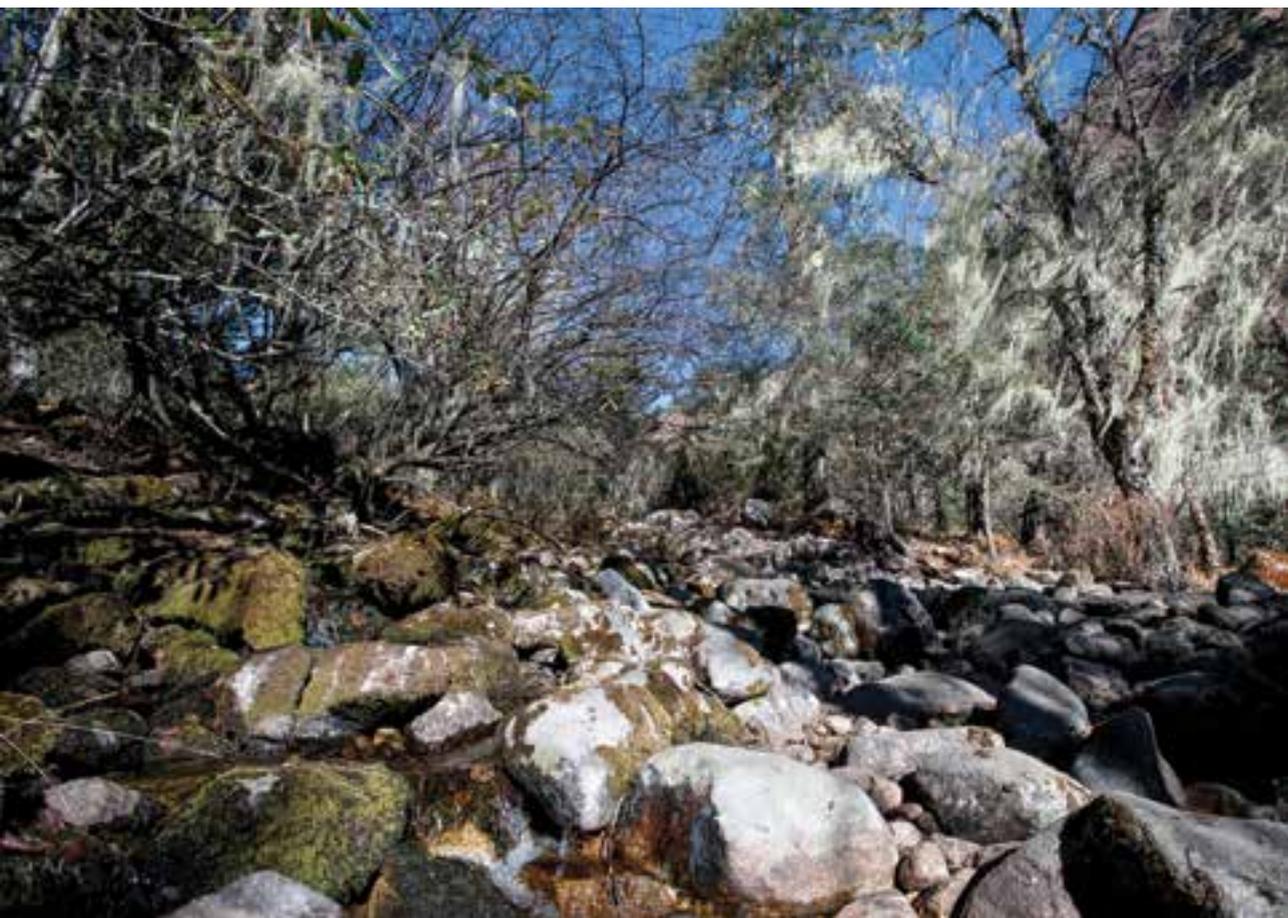
Annex

Table A1: **Useful open-source geospatial products for biomass estimation**

Geospatial Product	Satellite	Scale	Resolution (m)	Use
Land cover	MERIS	Regional	250	Vegetation stratification-forest type, forest crown cover
Land cover	MODIS	Regional	1,000	Vegetation stratification-forest type, forest crown cover
VCF Fields	MODIS	Regional	500	Works as proxy of biomass stratification
Ecoregion map	MODIS	Regional	10,000	
Deforestation	MODIS	Regional	500	Useful in estimation of temporal biomass changes
Phenology	MODIS	Regional	1,000	Useful in biomass estimation models
LAI	MODIS	Regional	500	Useful in biomass estimation models
Stand height	GLASNOST	Regional	500	Useful in biomass estimation models
Biomass	MODIS,GLASNOST	Regional	0.5x0.5	Useful in regional scale analysis
Deforestation	Landsat TM	National	30	Useful in estimation of temporal biomass changes
Land cover	Landsat TM	National	30	Forest stratification and field design development
Land cover change	Landsat TM	National	30	Useful in estimation of temporal biomass changes

Table A2: **Geospatial open-source datasets for biomass estimation**

Open Data	Satellite Sensor	Resolution (m)	Interval	Scale	Output
Multispectral reflectance data	MODIS	500	Fortnight	Regional	Forest cover, gap fraction,
	MERIS	500		Regional	Broad types
	MISR	500		Regional	
Vegetation index	MODIS	500	Fortnight	Regional	Seasonality, annual growth
	MERIS	250		Regional	
	MISR	500		Regional	
Multispectral reflectance data	Landsat TM	30	Month	National	Forest crown density, type, seasonality
Multispectral reflectance data	IRS AWiFS	56	5 days	National	
Very high resolution satellite data	Google Earth	1	> 1 year	Local	Crown projected area, age class
	Bhuvan	2.5	> 1 year	Local	Stand height
Allometric data	IPCC				Volume/biomass equations, BEFs
	FAO				
	Geowiicki				
Terrain data	SRTM	90			Elevation, slope, and aspect information
	ASTER	30			
	CARTODEM	10			

Table A3: **Cost comparison – satellite data**

	Satellite/Sensor	Resolution (m)	Swath (km)	Price per sq.km (USD)
Method 1	LISS-IV	5	70 (192 USD)	0.15*
	CARTOSAT -1	2.5	27 (129 USD)	1.02*
	CARTOSAT -2	1	9.6 (104 USD)	<1*
Method 2	RapidEye	5	77	1.28*
	IKONIOS	1		15
	GeoEye-1	0.5	15.2	40
	WorldView-2	0.5	16.4	32
	QuickBird	0.5	16.5	40

* Archive data price, may increase for new acquisitions

Assessment of Above Ground Biomass and Soil Organic Carbon Stocks in the Forests of India

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*F*orests play an important role in the global carbon cycle as carbon sinks in the terrestrial ecosystem. The carbon sequestered or stored in forest trees is mostly referred to in terms of the biomass. Estimating the amount of forest biomass is crucial for monitoring the amount of carbon that is lost or emitted during deforestation, and also provides an idea of a forest's potential to sequester and store carbon. The above ground biomass of the forest ecosystem at the national level is mainly estimated using allometric equations. Biomass equations for this have been developed for important species in all the physiographic zones in India. This article aims to summarize the methods used for estimating above ground biomass and soil organic carbon stocks in the Indian forest ecosystem. Total soil organic carbon stocks of 4,327.36 million tonnes and 4,680.25 million tonnes were estimated for 1995 and 2007, respectively. The estimate shows that due to the increase in forest cover, soil in Indian forests acted as a net sink for 352.89 million tonnes of carbon over the assessment period.

Keywords: above ground biomass, biomass estimation, biomass equation, soil organic carbon, forests

Introduction

India has stabilized its forest and tree cover, which covers about 24% of the total geographical area of the country. Forests play a vital role in the social, cultural, economic, and industrial development of the country as well as in maintaining its ecological security. They also provide great opportunities for adapting to climate change by increasing the resilience of people and ecosystems. Forests store a significant amount of carbon in the vegetation biomass, litter, dead wood, and soil, and this has a major role to play in climate change adaptation and mitigation. Soil carbon is the largest terrestrial carbon pool and plays a very important role in the carbon cycle. Biomass assessment is important for national development planning, as well as for scientific studies of ecosystem productivity and carbon budgets (Pandey et al. 2010; Parresol 1999; Zheng et al. 2004; Zianis and Mencuccini 2004). The importance of terrestrial vegetation and soil as significant sinks of atmospheric CO_2 and its other derivatives is highlighted under the Kyoto Protocol (Wani et al. 2010). Estimation of the accumulated biomass in the forest ecosystem is important for assessing the productivity and sustainability of

forest and enables us to estimate the amount of carbon dioxide that can be sequestered by forest from the atmosphere. Accurate forest biomass estimates are important for many applications such as timber extraction, and tracking changes in forest carbon stocks and the global carbon cycle. Forest biomass can be estimated through field measurements and remote sensing and GIS methods. Reliable estimation of total biomass for standing trees and forests and for components such as stem wood, stem bark, living and dead branches, foliage, stumps, and roots are all important for forest carbon assessment. Destructive harvesting of forest trees to obtain biomass estimates is not always possible because it is time-consuming and there is high risk of uncertainty. The most common approach is to obtain biomass estimates at standing level. Biomass is a function of diameter at breast height, tree height, and wood density at a given location. However, the contribution of these variables to the above ground biomass differs from site to site and for succession stages, disturbance levels, species composition, and others. Several attempts have been made to estimate biomass involving parameters such as DBH, tree height, and wood density or specific gravity with different regression equations; a strong relationship has been identified between biomass and these parameters (Rai and Proctor 1986).

Tiwari and Singh (1984) described a method for mapping biomass using black-and-white aerial photographs and ground survey data in a case study in the Kumaun Himalaya. Although, biomass inventories could be made using aerial photographs with minimum non-destructive sampling, it was impossible to identify individual subordinate species from the aerial photographs. Aerial coverage also doesn't provide sufficient data for generalizing the highly heterogeneous forest ecosystem across the country (Haripriya 2000). Rai and Proctor (1986) carried out a study in the Western Ghats to estimate the above ground tree biomass using harvesting and derived a regression equation relating the biomass fraction with the log transformation of DBH. Lodhiyal and Lodhiyal (2003) also carried out a study in the Bhabar forest in the central Himalayas to estimate biomass in 5-, 10- and 15-year old *Dalbergia sissoo* plantations using a selective harvesting technique. Twelve trees in each forest were harvested, and regression equations for each component were developed for biomass estimation. Mani and Parthasarathy (2007) developed an allometric equation to estimate the above ground biomass in the tropical dry evergreen forest of peninsular India. Mohanraj et al. (2011) used this equation to estimate the biomass and carbon stocks of different forest types in the Kolli hills in Tamil Nadu.

Many studies are also being carried out in India to estimate forest biomass and forest carbon stocks using remotely sensed data and GIS techniques. Aspect (direction of slope with respect to the sun), and slope (angle of geographical terrain) were observed to affect the biomass estimation of dry tropical forest (Bijalwan et al. 2010). Ramachandran et al. (2007) conducted a pilot study to estimate the carbon stocks in the natural forests of the Eastern Ghats of Tamil Nadu using GIS techniques and satellite data from IRS LISS III. In another study by Kale et al. (2009), the potential of the forests in the Western Ghats to sequester carbon dioxide was estimated using ground-based observation in combination with satellite remote sensing data from Landsat TM and IRS LISS III. Thakur and Swamy (2010) also estimated the forest biomass

of Barnawpara Sanctuary, Chattisgarh using remote sensing and ground data. They found a strong correlation between the C and N densities of the forest and NDVI and biomass.

The first estimates of the woody growing stock in India's forest were made by the Forest Survey of India (FSI) in 1995 using forest inventory data (1965–1990), thematic maps, and forest cover data. Sheikh et al. (2011) further estimated the carbon storage in India's forest biomass in 2003, 2005, and 2007 using secondary data on growing stock (ISFR 2003, 2005, 2009) combined with satellite data.

The values reported for total forest soil organic carbon stocks in India range from 23.4 to 47.5 Pg C (Dadhwal and Nayak 1993; Ravindranath et al. 1997; Dadhwal et al. 1998; Velayutham et al. 2000). Jha et al. (2003) reported that the Northeast states of India have a forest soil organic carbon store of 218 t carbon per hectare; a total of 3.73 million tonnes of soil organic carbon was estimated to be stored in the soil of rubber plantations in the northeastern region (Dey 2005). Chhabra and Dadhwal (2005) estimated the total soil organic carbon pool in Indian forests at 4.1 Pg C in the top 50 cm layer and 6.8 Pg C at one metre soil depth. As per FAO estimates (FAO 2005), the total forest carbon stocks in India increased over the 20 years from 1986 to 2005, and amount to 10.01 Gt carbon. IISc (2006) projected that carbon stocks would increase from 8.79 Gt carbon in 2006 to 9.75 Gt carbon in 2030 (IISc 2006), with forest cover becoming more or less stable, and new forest carbon accretions coming from the current afforestation and reforestation programme (Ravindranath et al. 2008). In India, CO_2 emissions from forest diversion or loss are largely offset by carbon uptake due to forest increment and afforestation. Many authors have concluded that in recent times, Indian forests overall have been a small source of carbon, with some regions acting as small sinks (Ravindranath et al.1997; Haripriya 2003; Chhabra and Dadhwal 2005; Ravindranath et al. 2008).

This article summarizes the methods used in the national forest inventory for estimating above ground biomass and soil organic carbon stocks in the forest ecosystem in India, and presents some recent results.

Methodology

Forest inventory

The national forest inventory uses a two stage sampling design. In the first stage, the country is divided into 14 physiographic zones based on physiography, climate, and vegetation: the Western Himalayas, Eastern Himalayas, North-Eastern Ranges, Northern Plains, Eastern Plains, Western Plains, Central Highlands, North Deccan, East Deccan, South Deccan, Western Ghats, Eastern Ghats, West Coast, and East Coast. Then 10% of all districts are selected for a detailed forest inventory, with the number in each zone determined in proportion to the size of the zone, and then districts selected at random within each zone. In the second stage, the selected districts are divided by latitude and longitude to form the

second stage sampling unit, and plots are laid out systemically in forest areas as follows. For each selected district, the Survey of India 1:50,000 topographic sheet is divided into 36 grids of 2.5′ x 2.5′ (minutes); each of these is further divided into four sub-grids of 1.25′ x 1.25′ to form the basic sampling units, and two of these are selected at random in each grid. The selected sub-grids form the sample. The intersection of the diagonals in the sub-grid is taken as the position for the centre of the sampling plot. A plot of 0.1 ha area is laid out on the ground for each plot falling in a forest area; all trees of DBH 10 cm and above within the plot are measured. Soil and forest floor data are collected from sub plots of 1 x 1 m laid out at each corner of the 0.1 ha plot. Data on herbs are collected from four square plots of 1 x 1 m, and shrubs (including regeneration) from four square plots of 3 x 3 m. These plots are laid out 50 m from the centre of the 0.1 ha plot in all four directions along diagonals in non-hilly areas and along trails in hill areas. In hill areas, plots are selected at random 2–10 m away from the trail on either side.

Above ground biomass

FSI has developed biomass equations for the important tree species in all the physiographic zones for estimating above ground biomass of small wood from trees with DBH 10 cm or more, biomass of foliage of trees with DBH 10 cm or more, biomass of small wood from trees with DBH less than 10 cm, and foliage of trees with DBH less than 10 cm. The biomass equations developed by FSI can be used to estimate the above ground biomass of the important tree species.

Soil organic carbon

Soil samples are collected from all the major forest types of India, classified as described by Champion and Seth (1968). Sub-Alpine, Moist Alpine Scrub, and Dry Alpine Scrub have been grouped into Sub-Alpine and Alpine Forest as no area statistics are available for these forest types. Thus soil organic carbon (SOC) data are collected for 14 major forest types. Soil samples have now been collected from almost every eco-region in the country that has forest cover, as well as from different density classes. Soil samples have also been collected from non-forest areas close to forest to enable estimation of the loss of SOC due to land conversion. A total of 657 soil samples have been collected and analysed; 556 from forest areas and the remainder from non-forest areas. The methodology includes reworking of NATCOM-I (First National Communication) forest soil carbon estimates by including more national datasets for soil carbon, including location and associated forest types, so as to get a reliable figure based on sources in the literature. These datasets have been harmonized and modified into a spatially distributed format according to the forest types of Champion and Seth (1968) so that they can be compared with current estimates.

Three sampling points were selected as replicates in each sampling unit. At each point, one soil sample was collected at a depth of 0–30 cm and one sample was collected from a non-forested area (agricultural) close to the major forest types. Forest floor litter was removed

from an area of 0.5 x 0.5 m at the sampling point and a 30 cm deep pit was dug out with area 30 x 50 cm. Soil was scraped from three sides of the pit over the whole depth from 0 to 30 cm, bulked, mixed thoroughly, and any gravel removed. A quarter of the bulked soil sample (approximately 500 g) was removed and placed in a polythene bag which was tightly closed with thread, and a second quarter was taken from the other side of the sample and stored in the same way. The soil samples were dried at room temperature in the laboratory. After drying, the samples were ground and sieved through a 100 mesh (2 mm) sieve. Soil organic carbon was estimated in the sieved samples using the standard method given by Walkley and Black (1934). The bulk density of the soil sample was determined using a core sampler method. The soil organic carbon stock was calculated from the formula given by Batjes (1996).

Results and Discussion

Estimation of the accumulated biomass in a forest ecosystem is important for assessing the productivity and sustainability of the forest. It gives an idea of the potential amount of carbon that could be emitted in the form of carbon dioxide when forests are cleared or burned, and helps in estimating the amount of carbon dioxide that could be sequestered from the atmosphere by a forest. Accurate assessments of forest biomass are needed in many applications. Forest biomass can be estimated through field measurement and remote sensing and GIS methods. There are two main methods of field measurement: destructive and non-destructive.

The destructive or harvest method is the most direct method of estimating the above ground biomass and carbon stock in a forest ecosystem. It involves harvesting all the trees in a known area and measuring the weight of the different components of each tree, like the tree trunk, leaves, and branches, and weights of samples of each after they are oven dried. This method of biomass estimation is limited to a small area or to small tree samples. The method enables accurate determination of the biomass for a particular area, but it is time and resource consuming, strenuous, destructive, and expensive, and is not feasible for large scale analysis.

The non-destructive method estimates the tree biomass without felling. The DBH of all trees is measured together with tree height. Standard values from published sources were used for the wood density. The woody volume per plot is estimated using volume equations and the biomass calculated using allometric equations. Since these methods do not involve felling, it is not easy to validate the reliability of the results. The allometric equations are developed and applied to forest inventory data to assess the biomass and carbon stocks of forests.

The Forest Survey of India (FSI) recently developed equations for estimating the biomass of the important species in the different physiographic zones in India, with separate biomass equations for the main stem, small wood, and foliage of trees with DBH 10 cm or more, and DBH less than 10 cm. The important species in the different zones are listed below.

Western Himalayas: *Pinus roxburghii, Quercus leucotrichophora, Rhododendron arboreum, Quercus semicarpifolia, Lyonia ovalifolia, Cedrus deodara, Abies pindrow, Shorea robusta, Mallotus philippensis, Tectona grandis, Acacia catechu, Machilus* spp., *Myrica esculenta*

Eastern Himalayas: *Quercus* spp., *Rhododendron* spp., *Macaranga* spp., *Alnus nepalensis, Rhododendron arboreum, Michelia* spp., *Ficus* spp., *Terminalia* spp., *Machilus* spp., *Eurya japonica*

North-Eastern Ranges: *Schima wallichii , Macaranga* spp., *Shorea robusta, Syzygium cumini, Careya arborea, Tectona grandis, Bauhinia* spp., *Toona ciliata, Ficus* spp., *Holarrhena antidysenterica*

Northern Plains: *Shorea robusta, Mallotus philippensis, Tectona grandis, Acacia catechu, Eucalyptus* spp., *Syzygium cumini, Dalbergia sissoo, Trewia nudiflora, Holarrhena antidysenterica, Diospyros melanoxylon, Bombax ceiba, Butea monosperma*

Eastern Plains: *Shorea robusta, Lagerstroemia speciosa, Amoora wallichii, Schima wallichii, Careya arborea*

Western Plains: *Anogeissus pendula, Wrightia tinctora, Boswellia serrata, Lannea coromandelica, Butea monosperma, Acacia lenticularis, Prosopis juliflora, Anogeissus latifolia, Prosopis cineraria, Acacia* spp., *Diospyros melanoxylon, Bauhinia* spp., *Holoptelea integrifolia, Salvadora oleoides, Acacia catechu, Holarrhena antidysenterica*

Central Highlands: *Acacia catechu, Anogeissus pendula, Boswellia serrata, Lannea coromandelica, Butea monosperma, Diospyros melanoxylon, Anogeissus latifolia, Terminalia crenulata, Mitragyna parviflora, Wrightia tinctoria, Zizyphus xylopyrus, Aegle marmelos, Acacia lenticularis, Madhuca latifolia, Miliusa tomentosa, Flacourtia indica*

North Deccan: *Tectona grandis, Terminalia tomentosa, Chloroxylon swietenia, Anogeissus pendula, Butea monosperma, Lannea coromandelica, Diospyros* spp., *Lagerstroemia parviflora, Buchanania lanzan, Madhuca longifolia, Acacia catechu, Gardenia resinifera, Wrightia tinctoria, Cleistanthus collinus, Syzygium cumini, Zizyphus xylopyrus, Aegle marmelos, Bauhinia variegate*

East Deccan: *Shorea robusta, Terminalia tomentosa, Buchanania lanzan, Lagerstroemia parviflora, Diospyros melanoxylon, Lannea coromandelica, Anogeissus latifolia, Madhuca indica, Chloroxylon swietenia, Tectona grandis, Butea monosperma.*

South Deccan: *Tectona grandis, Anogeissus latifolia, Terminalia tomentosa, Albizia amara, Chloroxylon swietenia, Dalbergia paniculata, Eucalyptus* spp., *Butea monosperma, Lagerstroemia lanceolata, Hardwickia binata, Wrightia tinctoria, Syzygium cumini.*

Western Ghats: *Tectona grandis, Anoegeissus latifolia, Terminalia tomentosa, Holarrhena antidysenterica, Terminalia paniculata, Macaranga peltata, Syzygium cumini, Schleichera oleosa, Myristica malabarica, Artocarpus heterophyllus, Pinus petula, Lagerstroemia lanceolata, Olea dioca, Aporosa lindleyana, Palaquium ellipticum, Xylia xylocarpus, Acrocarpus fraxinifolius.*

Eastern Ghats: *Anogeissus latifolia, Pterocarpus marsupium, Xylia xylocarpus, Lannea coromandelica, Albizia amara, Terminalia tomentosa, Syzygium cumini, Protium caudatum, Tectona grandia, Buchanania lanzan, Semecarpus anacardium, Memecylon angustifolium, Eucalyptus globulus, Grewia, tiliaefolia, Albizia* spp., *Chloroxylon swietenia, Diospyros melanoxylon.*

West Coast: *Terminalia tomentosa, Tectona grandia, Terminalia paniculata, Anogeissus latifolia, Lannea coromandelica, Wrightia tinctoria, Bombax ceiba, Terminalia belerica, Xylia xylocarpus, Careya arborea, Bridelia retusa, Boswellia serrata, Acacia catechu.*

East Coast: *Anogeissus latifolia, Chloroxylon swietenia, Hardwickia binata, Lannea coromandelica, Terminalia crenulata, Albizia amara, Boswellia serrata, Pterocarpus marsupium, Zizyphus xylopyrus, Dalbergia paniculata, Grewia* spp., *Dolichandrone falcata, Grewia tiliaefolia, Tectona grandis, Sterculia urens, Diospyros* spp., *Wrightia tinctoria, Acacia sundra.*

Forest soil organic carbon stocks (SOC) were estimated for different forest types from the soil organic carbon density for that forest type and total area of forest type in 1995 and 2007. The results are shown in Table 1.The soil organic carbon stocks for 2007 were estimated by summing the stocks estimated for different forest types; the soil organic carbon stocks for land converted to forest were estimated using the value for soil organic carbon density of non-forest areas. Tropical Moist Deciduous Forest had the largest stores of carbon in soil (1,666 million tonnes), and Himalayan Dry Temperate Forest the least (3.85 million tonnes). The total soil organic carbon stock was 4,328 million tonnes in 1995 and 4,680 million tonnes in 2007. The results indicate that as a result of the increase in forest cover, the soil in Indian forests acted as a net sink for 353 million tonnes of carbon during the assessment period.

The findings are consistent with the total soil organic carbon pools estimated in Indian forests by Chhabra and Dadhwal (2005). The estimation of soil organic carbon stock has considerable uncertainty due to various factors. An uncertainty of 8.6% is attributed to the number of soil samples taken for the different forest types, of 15.0% to the organic carbon estimation method used (Walkley and Black 1934), and 5.5% to the estimation in bulk density of soils.

The carbon stocks in different forest carbon pools in India's Himalayan states are shown in Table 2.

Table 1: **Estimated forest soil organic carbon stocks for 1995 and 2007**

Forest type	Soil organic carbon stock (million tonnes)		Changes in soil organic carbon stock (million tonnes)
	1995	2007	
Himalayan Dry Temperate Forest	3.63	3.85	0.23
Himalayan Moist Temperate Forest	132.26	143.13	10.87
Littoral and Swamp Forest	28.03	30.02	1.99
Montane Wet Temperate Forest	121.23	130.92	9.69
Sub-Alpine and Alpine Forest	243.49	263.49	20.01
Sub-Tropical Broad Leaved Hill Forest	12.20	13.07	0.87
Sub-Tropical Dry Evergreen Forest	12.05	13.10	1.05
Sub-Tropical Pine Forest	130.83	141.55	10.72
Tropical Dry Deciduous Forest	1,453.64	1,572.38	118.74
Tropical Dry Evergreen Forest	12.09	13.06	0.96
Tropical Moist Deciduous Forest	1,539.73	1,665.65	125.91
Tropical Semi-Evergreen Forest	153.18	165.35	12.17
Tropical Thorn Forest	282.72	305.73	23.02
Tropical Wet Evergreen Forest	202.28	218.95	16.67
Total	**4,327.36**	**4,680.25**	**352.89**

Source: ICFRE 2013

Table 2: **Carbon stocks in different forest carbon pools in India's Himalayan states**

State	Carbon stock in different carbon pools ('000 tonnes)						C stock (tonnes/ha)
	Above ground biomass	Below ground biomass	Dead wood	Litter	Soil	Total	
Arunachal Pradesh	234,110	52,489	3,753	16,080	656,444	962,876	142.07
Assam	44,543	10,240	1,050	5,411	107,680	168,924	61.10
Himachal Pradesh	63,436	16,718	525	2,367	78,178	161,224	112.20
Jammu & Kashmir	96,096	26,259	745	3,106	115,505	241,711	113.62
Manipur	26,125	8,545	503	3,828	99,152	138,153	80.86
Meghalaya	23,191	6,333	789	4,924	113,861	149,098	87.77
Mizoram	15,851	3,273	656	2,743	75,405	97,928	52.41
Nagaland	16,578	4,273	586	2,547	105,894	129,878	94.67
Sikkim	10,512	3,013	156	456	25,595	39,732	121.8
Tripura	14,142	2,909	515	1,595	39,756	58,917	72.25
Uttarakhand	106,354	27,499	1,255	5,655	144,927	285,690	116.88

Source: FSI n.d.

Conclusion

Forests contain the largest carbon pool on earth. They act as a major natural source and sink of carbon and thus have the potential to be a major component in the mitigation of global warming and to play a major role in adaptation to climate change. Estimation of forest biomass and carbon stocks will enable us to assess potential carbon loss during deforestation as well as the amount of carbon that a forest can store when conserved. Although numerous studies have been carried out to estimate forest biomass and forest carbon stocks, there is still a need to develop robust GIS based methods to quantify the estimates for the forest ecosystem more accurately.

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Bhutan's Geospatial Information System for Forest Biomass Assessment

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This paper provides an overview of the rapidly advancing geospatial technology now used for forest biomass assessment in Bhutan within the broader framework of national strategies and programmes. The forest biomass assessment uses data from the national land use land cover mapping activity as baseline information. The National Forest Inventory is also expected to provide data needed for estimation of forest biomass and carbon stocks. The paper describes the current practices and the proposed scope of the geospatial information system to be used for forest biomass based on the Readiness Preparation Proposal (R-PP) for Bhutan from 2013. Developing appropriate geospatial technology remains a challenge for the assessment of forest biomass in Bhutan.

Keywords: forest biomass assessment, Bhutan geospatial information system, national forest monitoring

Introduction

Bhutan is a landlocked country in the eastern Himalayas lying between 88°45' and 92°10' E and 26°40' and 28°15' N and with a total geographic area of 38,394 km². The elevation ranges from 200 masl in the south to more than 7,000 masl in the north, and the climate varies with altitude. The country is divided into 20 districts (dzongkhags, local government level), and 205 sub-districts (gewogs, grassroots level). The population in 2005 was 634,982, giving an overall population density of 16 persons per square kilometre; 69% live in rural areas and 31% in urban areas (NSB 2005). According to the Department of Forests and Parks Services, Ministry of Forest and Agriculture, 19,677 km² of land (51% of the total area) has protected status, with 16,396 km² within nine protected areas and 3,307 km² in 12 biological corridors (areas set aside to connect one or more protected areas and conserved and managed for the safe movement of wildlife). Bhutan has four major river systems: the

Drangme Chhu; the Puna Tsang Chhu, also called the Sankosh; the Wang Chhu; and the Amo Chhu. The country is rich in natural resources.

The Forest Department was one of the first government agencies in Bhutan to use a system for recording geospatial information. This paper provides an overview of the rapidly advancing geospatial technology now used for forest biomass assessment in Bhutan within the broader framework of national strategies and programmes. The paper also looks at the proposed REDD+ (Reducing Emissions from Deforestation and Forest Degradation) programme in Bhutan as a future opportunity, and describes the current practices and proposed scope of the geospatial information system to be used for forest biomass based on the Readiness Preparation Proposal (R-PP) for Bhutan from 2013.

Current Basis for the Geospatial Information System for Forest Biomass Assessment in Bhutan

Land use land cover mapping

Bhutan's national land use land cover mapping exercises provide baseline information for the forest biomass assessment.

In the 1960s and 1970s, Bhutan developed the first national forest classification map using analogue aerial photo interpretation and cartographic drawings.

In 1993/94, the Land Use Planning Project (LUPP) mapped national land use and land cover using a digital remote sensing methodology based on panchromatic SPOT imagery from 1989 with field verification (LUPP 1997). The land use polygons were digitized through visual interpretation of the SPOT satellite images and the results were recorded using GIS (geographic information system). Figure 6 shows the LUPP land use land cover map of Bhutan published in 1995. The LUPP classification described forest cover according to forest type and density class and was available in digital format.

The LUPP was further refined in the Land Cover Mapping Project (LCMP) implemented from 2008 to 2010 (NSSC 2010); the land classification system was revised in 2002 and 2009. LCMP used digital image processing of multispectral ALOS (Advanced Land Observation System) images (AVNIR-2) with 10 m resolution. The minimum accuracy was set at 85%. Figure 7 shows the LCMP 2010 land use land cover map of Bhutan. THE LCMP provided up-to-date and reliable spatial base data for forests and other land use.

Forest inventory

The land use land cover mapping exercises provide spatial information on forest cover according to forest type and are used as a base for estimation of forest statistics, including carbon stocks. Further initiatives by the Forest Department provide the detailed information needed for these estimations. The area data are complemented by ground assessments

Figure 6: **The LUPP 1995 land use land cover map of Bhutan**
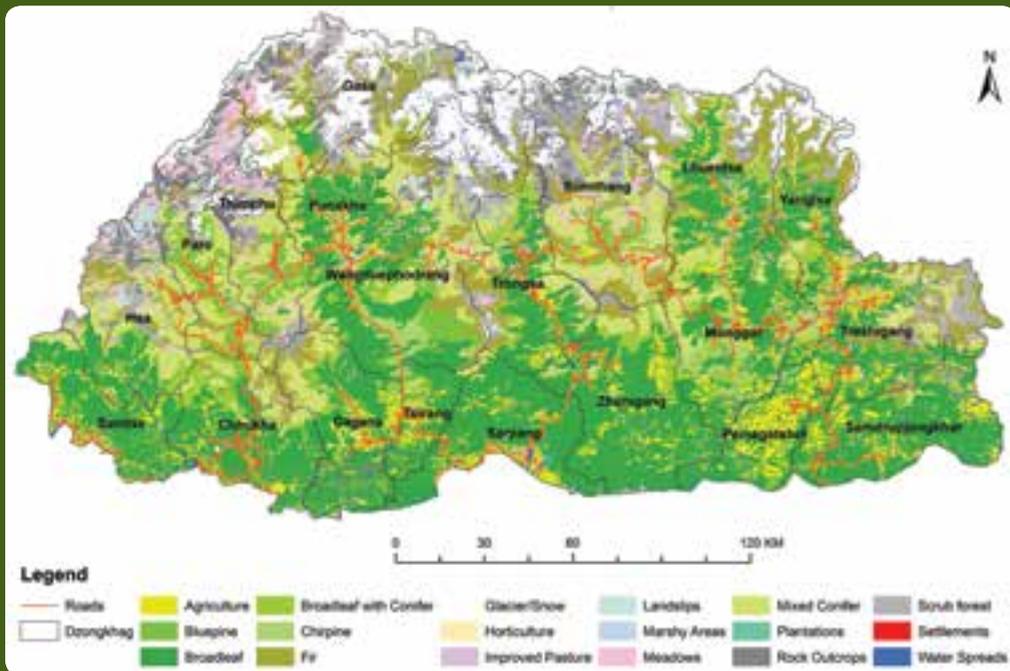
Figure 7: **The LCMP 2010 land use land cover map of Bhutan**
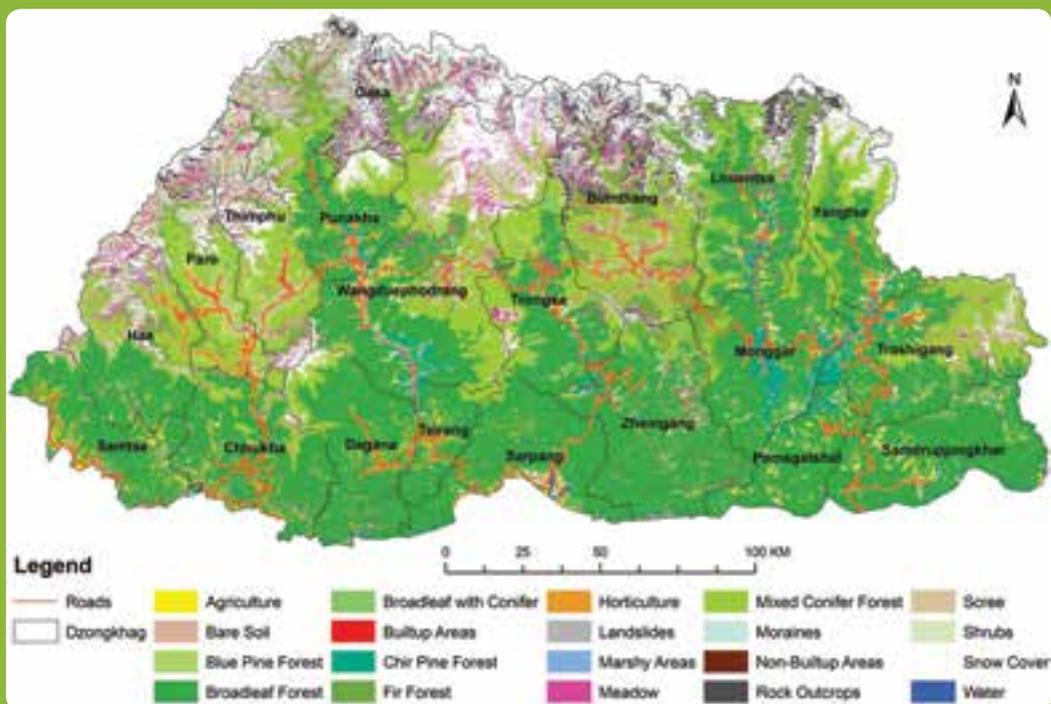
carried out through the Bhutan National Forest Inventory, which is designed to assess forest growing stock as a basis for planning for sustainable management of the forest resources. The National Forest Inventory is also being designed to provide estimates of forest biomass and carbon stocks. Under the National Forest Inventory , field measurements of tree data are carried out in 0.05 ha nested circular sample plots (12.62 m radius). Small trees and saplings (regeneration) are recorded in a sub-plot of 3.57 m radius; and data on other vegetation in a plot of 0.57 m radius. The variables required to determine forest understory carbon stock are measured in 5 m^2 sample plots laid out 20 m southwest of the centre of the main plots. In the future, tree carbon stocks will be estimated using species-specific volume and mass equations determined using randomized branch sampling (RBS).

The Forest Department is also implementing a Tree Crown Cover (TCC) 2012 programme in partnership with the US Forest Service to map forest cover in Bhutan through identification of crown cover in satellite images. Figure 8 shows an initial output from the initiative.

Future Development of the Geospatial Information System for Forest Biomass Assessment in Bhutan

In 2011, Bhutan joined the UN-REDD Programme. The Watershed Management Division, under the Department of Forests and Park Services, Ministry of Agriculture and Forest, was

Figure 8: **The 2012 tree crown cover map of Bhutan**
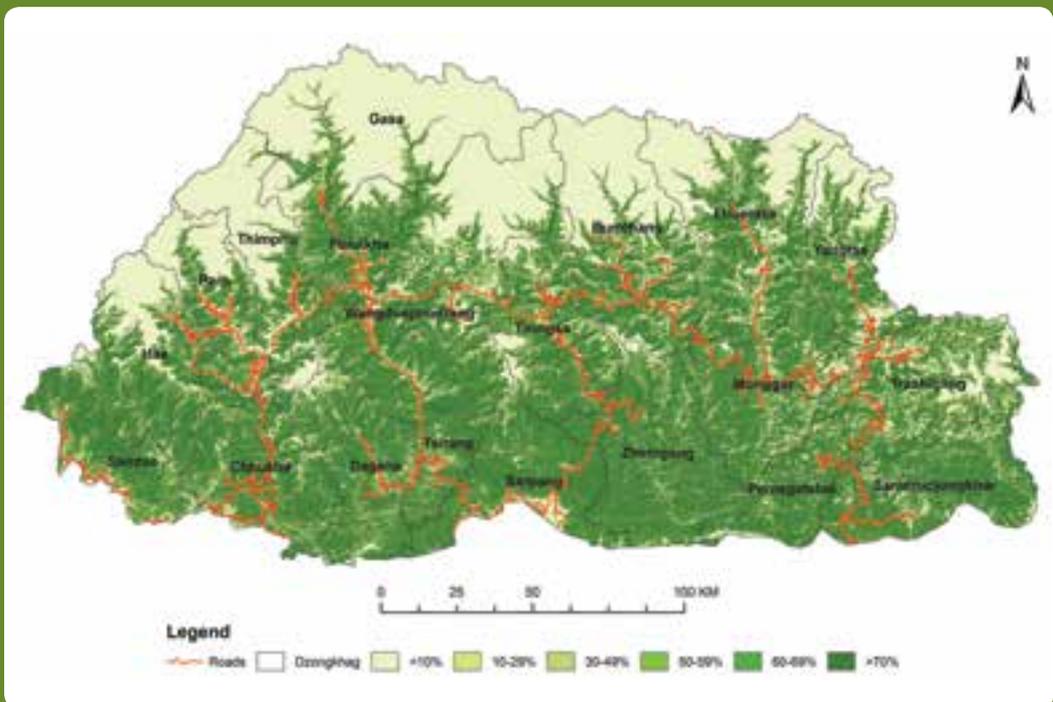
designated as the focal point for REDD+. A Readiness Preparation Proposal (R-PP) for Bhutan has been submitted but not yet approved (DOFPS 2013). Once the R-PP programme is accepted it will be necessary to implement a holistic forest information system for the country. The R-PP proposes that the Forest Department establishes a REDD+ Information System and Activity Registry. The information system will function as the national centre for REDD+ knowledge management for both local and international stakeholders.

Bhutan plans to follow the UN-REDD National Forest Monitoring System (NFMS) strategy within the R-PP framework. This includes a satellite land monitoring system (SLMS) for a) monitoring of REDD+ activities, and b) generating activity data to feed into the national GHG inventory, which requires national analysis of land use change based on the IPCC categories and methodologies.

In addition to the non-spatial information system, the Bhutan R-PP proposes a web-GIS portal for sharing of forest monitoring data and information at national and international levels. Any internet user will be able to view forest information through a GIS mapping interface, including forest area and types, statistics on deforestation, and forest governance structures.

Gaps in the geospatial information system

There are a number of implementation gaps in the geospatial information system for forest biomass assessment in Bhutan. The overall methodology for the national forest monitoring system and satellite land monitoring system has yet to be developed. In addition, factors such as the density of major forest types, root to shoot ratios, and conversion factors for biomass to forest carbon, which are required for estimating forest biomass, still need to be determined.

There are a number of ongoing activities that are potentially relevant for forest biomass assessment and forest monitoring, such as tree canopy mapping, National Forest Inventory , Forest Resources Potential Assessment, and randomized branch sampling, but linkages still need to be made between these initiatives and the geospatial forest information system.

International linkages

Bhutan, in collaboration with the International Centre for Integrated Mountain Development (ICIMOD), has developed a harmonized land cover classification system for Bhutan. This dataset could also provide a source for forest biomass assessment. In the Bhutan-ICIMOD study, a change matrix was used to identify changes in terms of deforestation and reforestation or regeneration. There was a small change in 'forest to non-forest' from 1990 to 2000, zero change between 2000 and 2010, and close to zero (-2 km^2) over the whole period. The change in 'non-forest to forest' was more marked, with a net increase of 1,174 km^2 between 1990 and 2010, equivalent to an average annual increase of 59 km^2 or 0.2% (Gilani et al. 2015).

The Forest and Agriculture Organization (FAO) Forest Resource Assessment (FRA) reported a constant annual 0.34% increase in Bhutan's forest from 1990–2000, 2000–2005, and 2005–2010, with no deforestation (FAO 2010). A forest resource assessment report was submitted as required by FAO as a part of the Global Forest Resources Assessment 2015 (MOAF 2013). However, there was a major constraint to the reporting of biomass and the carbon estimation for Bhutan resulting from the outdated values for growing stock and lack of specific wood density and biomass expansion factors.

Conclusion

Developing appropriate geospatial technology remains a challenge for the assessment of forest biomass in Bhutan. The adaptations to geospatial techniques proposed within the framework of the Bhutan R-PP proposal in line with IPCC guidelines need to be implemented. A part of the data gap could be filled by linking to the randomized branch sampling initiative and developing biomass equations. Further gaps in the geospatial system for assessment of forest biomass could be filled by designing linkages to integrate the ongoing collection of field data. There is also a need to develop protocols for Bhutan's geospatial information system in line with overall strategies and international standards.

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Forest Biomass Assessment in India

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*D*ata from the national forest inventory conducted between 2002 and 2008 were analysed to assess the carbon in India's forests. The survey was conducted in selected districts at randomly selected points after ascertaining the optimum number of plots required for each combination of forest type and forest density. The exact geographical locations of the optimum number of randomly selected sample plots were visited, dead wood above 5 cm in diameter, all woody litter, and all shrubs and climbers were uprooted, weighed, and recorded. Dry biomass was converted to carbon stock. A GIS technique was used to intersect the forest type map (2004) and forest cover maps (1994 and 2004) to give two maps each with 45 strata, one for each year. The map for 1994 was overlaid on the map of 2004 to estimate the area of remaining forest and non-forest land converted to forest for each forest type and canopy density category. By multiplying the activity data with these factors, parameter-wise total carbon values were calculated for all 45 strata; these were combined into five carbon pools. National carbon estimates for 1994 and 2004 were obtained by adding the pool-wise carbon content for the individual years. The Forest Survey of India (FSI) plans to introduce a five-year cycle for forest inventory and to replace the single square plots used up to now for field measurements with a cluster of circular plots. Inclusion of new variables is also contemplated so that newer parameters can be estimated.

Keywords: forest cover mapping, forest type mapping, national forest inventory, biomass study

Introduction

Understanding of the present situation and future requirements provides the basis for any planning related to renewable and non-renewable natural resources and drives the information needs for planning. Often surveys are used to generate the desired information with the desired level of accuracy and precision.

After Indian independence in 1947, huge areas of forest came under the control of the government. Thus the National Forest Policy of 1952 emphasized forest survey and demarcation, together with other aspects of forest management and development. As this was an era of industrial development, the forestry sector of the Government of India also attempted to augment wood-based industries. With this in view, a 'Pre-Investment Survey of Forest Resources' project was undertaken in 1965 by Government of India in collaboration with UNDP and FAO. Three regions were selected that contained forests with tree species of industrial importance.

The late 1970s and early 1980s were very important globally in terms of the forest scenario, and a paradigm shift became visible in attitudes towards the role of forest resources. The forests, which had seemed to be an inexhaustible resource, were rapidly depleting under the pressure of growing populations of humans and cattle. As a result, strategies were developed to focus attention more on conservation forestry than on production forestry.

During the 1990s, understanding of the role played by forests increased and additional parameters like carbon sequestration in vegetation and forest soil, biological diversity, regeneration status of plant species, non-wood forest products, and others became central in all deliberations related to forest resources. Taking this as an opportunity, the Forest Survey of India (FSI) initiated a National Forest Inventory (NFI) programme in 2002/03 with the aim of capturing such parameters in a two-year cycle. This approach is still being followed and the estimates are being improved cycle by cycle. According to the 'Good Practice Guidance for Land Use, Land-Use Change and Forestry' of the Intergovernmental Panel on Climate Change (IPCC 2003), estimation of biomass, and thus carbon, requires activity data on the extent of forest and emission factors. This paper discusses the collection of activity data and estimates of carbon stock in India, and especially in the states that mainly lie within the Himalayan region.

Methodology

Estimating activity data

Three different methods for estimating activity data are advocated in GOFC-GOLD (2010) and are being used by different countries to assess the area under 'forest land remaining

forest' and 'non-forest land converted to forest.' The methodologies are wall-to-wall mapping using remote sensing data, mapping of sampled areas using remote sensing data, and field survey methods.

FSI has been assessing the forest cover of India using remote sensing data on a biennial basis since 1987 (FSI 2012a); a hybrid approach is used that combines an automated digital classification technique with visual interpretation. This technique is simple, robust, and cost-effective.

Stratification of the forest area

To increase the precision of estimates for a heterogeneous population, stratification is carried out using selected stratification variables to divide it into relatively homogeneous sub-populations. In the case of forest biomass assessment, the principal variable, the carbon stored in the vegetation, depends largely upon canopy density and forest type, thus these two parameters were considered for use as stratification variables.

Forest type mapping

Information on the extent of forest cover by type provides the basis for characterizing the forests in terms of floristic composition and ecological value. FSI has recently completed mapping of the forest types of India according to the Champion & Seth Classification (GOI 1968) at a scale of 1:50,000. The forest type maps were used to determine the distribution of cover of different forest types in India. In the project described here, 14 forest type groups covering 174 forest types and one plantation group were used for carbon stock estimation. Using this classification, area statistics (activity data) were generated using a GIS technique for the two categories: forest land in 1994 that remained forest land in 2004, and non-forest land in 1994 that had become forest land by 2004.

Estimating emission factors

The FSI used a stock-difference method (inventory based approach or periodic accounting) to estimate various emission factors as recommended by the good practice guidance of the IPCC. This enables estimation of the change in carbon stocks over time and thus the exchange of greenhouse gases between the forest ecosystem and the atmosphere.

FSI has been using a multistage sampling approach to carry out the national forest inventory under the NFI programme. Data were collected from about 21,000 sample plots between 2002 and 2008. The sample size for forest biomass assessment was chosen following an National Forest Inventory pilot survey conducted in 1995/96. The plot sizes used (0.1 ha for wood volume, 3 x 3 m for shrubs, and 1 x 1 m for herb biomass) are well established in India. Twenty important tree species were identified for the 14 strata (forest type groups) in the NFI and evaluated separately in the biomass calculations.

The method is described below.

Above ground biomass of trees with DBH ≥10 cm and bamboo

All trees of diameter 10 cm and above were measured in each sample plot. The above ground woody volume was calculated per plot using volume equations developed by FSI for the different species with the volume of the main stem measured above 10 cm diameter and volume of all branches with a diameter of 5 cm or more. Data for the specific gravity and percentage carbon content of most of the tree species were obtained from the published literature. For a few species, the percentage carbon content was ascertained by experiment; the average of the known species was used for those remaining. Standard formulae were used to calculate the biomass and carbon content of each tree.

The volume of bark was estimated from the double bark thickness of trees measured in the forest inventory and the tree volume equations. Bark volume equations were developed using species-wise diameter at breast height (DBH, height taken as 1.37 m) and bark thickness, adjusted for 'bark void factor', and used to estimate the bark volume. The carbon stored in the bark was estimated using the carbon content percentage of wood.
Biomass equations were developed for small wood and foliage for each of the species except for palm-like trees. Three normal trees in each 10 cm diameter-class interval were selected and measurements of the diameter, height, crown length, crown width in two directions, blanks in canopy, and shape of the crown were recorded for each tree. One normal tree was selected in each diameter class of each species and a partially destructive method was used to compute the biomass of woody branches up to 5 cm diameter, of twigs, and of leaves, separately. (A partial method was used as there were restrictions on whole tree felling or lopping.) The volumes were converted into biomass using the specific gravity. Biomass equations were developed for each species taking the dry biomass of small wood and foliage as the dependent variable and DBH as the independent variable. Bamboo biomass and carbon stock were also calculated from the NFI data. The total above ground biomass (AGB) and carbon content of trees with DBH ≥10 cm were calculated at the plot level using the plot level data from the NFI and species-wise carbon content.

AGB of trees with DBH <10 cm

Three trees of DBH 1 to 9 cm were felled for each of the 20 species and the biomass values of wood, twigs, and leaves calculated and recorded in the prescribed format. Biomass equations were developed for each species taking the dry biomass of wood and foliage as the dependent variable and DBH as the independent variable. The total biomass and carbon content of trees with DBH <10 cm were calculated at plot level using the regeneration data from the NFI, i.e., recruits, unestablished, and established regeneration for all trees with a DBH between 5 and 10 cm.

AGB of shrubs, herbs, and climbers, and biomass of dead organic matter

The data from the forest inventory conducted from 2002 to 2008 were first analysed to ascertain the optimum number of plots required for each combination of forest type and canopy density. The results showed that 15 clusters of two sample plots for each combination would be sufficient for estimating the biomass and carbon factors for shrubs, herbs, and climbers, and dead organic matter, with a 30% permissible error. (These components contribute very little to total carbon pools; moreover, since 2010 this has become part of the regular inventory and the estimates will be improved continuously.) The survey was conducted at randomly selected points in the districts that had been inventoried between 2002 and 2008 and for which forest type and canopy density were known.

The exact geographical locations (latitude and longitude) of the optimum number of randomly selected sample plots for the desired combinations of forest type and canopy density were visited. Taking latitude and longitude as the centre of the sample point, three concentric plots of size 5 x 5 m, 3 x 3 m, and 1 x 1 m were laid out at a distance of 30 m from the centre of the sample point in north and south directions. In the 5 x 5 m plot, all dead wood ≥5 cm diameter was collected, weighed, and recorded. In the 3 x 3 m plot, all woody litter (branches <5 cm diameter) was collected, weighed, and recorded, and all shrubs and climbers were uprooted, weighed, and recorded. In the 1 x 1 m plot, all herbs were uprooted, weighed, and recorded. The dry biomass was converted to carbon stock.

Organic matter in soil and forest floor

Data on the forest floor (non-woody litter and humus) and soil carbon are also collected from each sample plot during the forest inventory. For humus and soil carbon, two sub-plots of 1 x 1 m are laid out within the main plot. The forest floor from both plots is first swept and weighed and a portion of the same kept for carbon analysis. A pit of 30 x 30 x 30 cm is dug at the centre of each sub-plot and a 200 g composite sample of soil kept for organic carbon analysis. Samples of soil and humus analysed at standard soil laboratories were used in the calculations.

Below ground biomass

Below ground biomass (roots) is one of the most difficult components to measure. It is not generally measured in the forest inventory but is included through a relationship to AGB (usually a root-to-shoot ratio) established by various researchers. The IPCC good practice guidance also provides default ratios for six major global forest types. The FSI selectively used these defaults to assess the carbon content of below ground biomass.

Quality assurance and quality control

Quality assurance is a process which a surveying and assessing institution puts in place to assure the quality of a product prior to implementation of the work. It includes defining the

objective(s) and all the terms and concepts, designing the work plan, preparation of working manuals, capacity building of the officials involved, testing of the procedures developed before finalization, preparation of the regression equations and indices using validation, and use of suitable factors (e.g., carbon content, wood density). The forest carbon stock estimation carried out by FSI uses four products: forest cover maps, forest type maps, NFI datasets, and results of biomass study (for developing biomass expansion factors). All these products have been generated following strict quality assurance processes specifically developed for the assured performance of each.

Quality control is the process put in place to control the errors which may arise during the implementation of the work, i.e., during the acquisition, collection, and recording of data; coding; data entry; data processing; interpretation of results; and others. Separate quality control processes are developed and put in place for each programme and each of the errors mentioned above for an assured quality product.

The second level of a quality assurance process is an independent verification procedure carried out by a third party arranged by the implementing agency before reporting to the UN Framework Convention on Climate Change (UNFCCC) or other approving agency. This process ensures the transparency and suitability of the procedures adopted for the whole process, i.e., from designing to the final estimation protocols. The forest carbon stock report in this project was sent to 15 experts of known reputation; their suggestions were incorporated as appropriate.

Synthesis

A GIS technique was used to intersect the forest type map (2004) with the forest cover maps (1994 and 2004) to give two maps each with 45 strata (forest type and canopy density intersections), one for each year. The map for 1994 was overlaid on the map of 2004 to estimate the area of remaining forest and non-forest land converted to forest for each forest type and canopy density category. The areal extent of individual strata was estimated using a GIS technique. The geographical location of each NFI sample plot was recorded by GPS during field visits. These locations helped in creating a GIS compatible point layer of the forest inventory plots. This NFI point layer map was overlaid on the maps with the 45 forest type and canopy density strata. The NFI points falling in each stratum were identified (FSI 2011a). For each stratum, the plot wise information on all the parameters for each carbon pool was aggregated to give a generalized factor for that stratum. Some biomass and carbon factors like shrubs, herbs, climbers, dead wood, and woody litter were specifically developed for each stratum. By multiplying the activity data with these factors, parameter-wise total carbon values were calculated for all 45 strata, these were combined into five carbon pools.

National carbon estimates for 1994 and 2004 were obtained by adding the pool-wise carbon content for the individual years. The difference gave the net removal of carbon as shown in Table 3 (FSI 2012b).

Table 3: **Change in carbon stock of forest land between 1994 and 2004**

Component	Carbon stock of forest land in 1994	Carbon stock of forest land in 2004	Net change in carbon stock
	(million tonnes)	(million tonnes)	(million tonnes)
Above ground biomass	1,784	2,101	317
Below ground biomass	563	663	100
Dead wood	19	25	6
Litter	104	121	17
Soil organic matter	3,601	3,753	152
Total	**6,071**	**6,663**	**592**

Results

Himalayan states

Carbon estimates were not worked out specifically for India's Himalayan region. However, pool-wise carbon estimates were made for 2004 for the forest areas of the five states that mainly lie within the Himalayan region. The results are shown in Table 4 (FSI 2012b).

Soil organic matter has the largest stock of carbon in all five states, with 48 to 68% of the total (cf. national average of 56%), followed by AGB, ranging from 24 to 40% (national average 32%), and below ground biomass, ranging from 6% to 11% (national average 10%).

The detailed estimates of carbon stored in vegetation in terms of the two stratification variables (canopy density and forest type) in the five Himalayan states are summarized in the following. The overall national average of carbon stock per hectare was 169.0 t, 121.8 t, and

Table 4: **Pool-wise carbon estimates for 2004 in India's major Himalayan states**

Component	Unit	Major Himalayan states					Total
		Arunachal Pradesh	Himachal Pradesh	Jammu & Kashmir	Sikkim	Uttarakhand	
Area	km²	67,777	14,369	21,273	3,262	24,442	**131,123**
Above ground biomass	'000 t	234,110	63,436	96,096	10,512	106,354	**510,508**
Below ground biomass	'000 t	52,489	16,718	26,259	3,012	27,499	**125,977**
Dead wood	'000 t	3,753	525	745	156	1,255	**6,434**
Litter	'000 t	16,080	2,367	3,106	456	5,655	**27,664**
Soil organic matter	'000 t	656,444	78,178	115,505	25,595	144,927	**1,020,649**
Total carbon stock	'000 t	962,876	161,224	241,711	39,731	285,689	**1,691,231**
Carbon stock	t/ ha	142.07	112.20	113.62	121.80	116.88	**128.98**

58.3 t for very dense forest (canopy density above 70%), moderately dense forest (canopy density between 40 and 70%) and open forest (canopy density between 10 and 40%), respectively.

Arunachal Pradesh

Arunachal Pradesh lies between the outer Himalayas and Patkoi ranges and is mostly hilly; the elevation ranges from 100 to 7,300 masl (FSI 2011b). With respect to canopy density, the carbon stock per hectare was 204.8 t, 136.0 t, and 98.3 t for very dense forest, moderately dense forest, and open forest, respectively. Tropical Semi-Evergreen Forests constitute the highest percentage of forest cover in the state (68.8%) and have a carbon stock of 154.1 t/ha; Tropical Wet Evergreen Forests constitute 1.5% of the state's forest cover and have a carbon stock of 176.4 t/ha. The national average for Tropical Semi-Evergreen Forests – North East is 110.1 t/ha and for Tropical Wet Evergreen Forests – North East 117.7 t/ha (FSI 2012b).

Himachal Pradesh

Himachal Pradesh is largely hilly and divided into the outer Himalayas or Siwaliks, the lesser Himalayas or Central Zone, and the great Himalayan and Zanskar or Northern Zone. About 33% of the total geographical area of the state has permanent snow cover (FSI 2011b). With respect to canopy density, the carbon stock per hectare was 184.9 t, 130.6 t, and 71.0 t for very dense forest, moderately dense forest, and open forest, respectively. Himalayan Moist Temperate Forests (part of the re-grouped 'Montane Moist Temperate Forest' in this study) constitute the highest percentage of forest cover in the state (44.2%) and have a carbon stock of 139.5 t/ha; Himalayan Dry Temperate Forests and Sub-Alpine Forests (re-grouped as 'Sub-Alpine and Dry Temperate Forests' in this study) constitute 12.2% of the state's forest cover and have a carbon stock of 141.2 t/ha. The national average for these two forest types (re-grouped) is 127.2 and 119.2 t/ha, respectively (FSI 2012b).

Jammu and Kashmir

Jammu and Kashmir lies mainly in the Himalayan Mountains and is comprised of sub-mountain and semi-mountain plains (kandi or dry belt), the Siwaliks, the high mountain zone (Kashmir Valley, Pir Panjal range and its offshoots), and the middle run of the Indus River (Leh and Kargil); the elevation ranges from 227 to 7,586 masl (FSI 2011b). With respect to canopy density, the carbon stock per hectare was 202.9 t, 132.9 t, and 80.8 t for very dense forest, moderately dense forest, and open forest, respectively. Himalayan Moist Temperate Forests (part of the re-grouped 'Montane Moist Temperate Forests' in this study) constitute the highest percentage of forest cover in the state (34.4%) and have a carbon stock of 111.9 t/ha; Moist Alpine Scrub and Dry Alpine Scrub (re-grouped as 'Alpine Scrub' in this study) constitute 11.6% of the state's forest cover and have a carbon stock of 155.3 t/ha. The national average for these two forest types (re-grouped) is 127.2 and 133.2 t/ha, respectively (FSI 2012b).

Sikkim

Sikkim mainly comprises a young mountain system encompassing the Lesser Himalayas, Central Himalayas, and Tethys Himalayas. The elevation ranges from 300 to 8,500 masl, and this together with high rainfall results in a varied climate from tropical to tundra (FSI 2011b). With respect to canopy density, the carbon stock per hectare was 239.4 t, 119.9 t, and 57.4 t for very dense forest, moderately dense forest, and open forest, respectively. Montane Wet Temperate Forests and Himalayan Moist Temperate Forests (re-grouped as 'Montane Moist Temperate Forests' in this study) constitute the highest percentage of forest cover in the state (31.2%) and have a carbon stock of 135.9 t/ha; Himalayan Dry Temperate Forests and Sub-Alpine Forests (re-grouped as 'Sub-Alpine and Dry Temperate Forests' in this study) constitute 27.0% of the state's forest cover and have a carbon stock of 145.2 t/ha. The national average for these two forest types (re-grouped) is 127.2 t/ha and 119.2 t/ha respectively (FSI 2012b).

Uttarakhand

Uttarakhand is largely hilly (about 90%) with a temperate climate and is divided into three physiographic zones – the Himalayas, the Siwaliks, and the Terai. The elevation ranges from below 300 m in the Terai region to above 4,500 m; around 19% of the total geographical area of the state has permanent snow cover (FSI 2011b). With respect to canopy density, the carbon stock per hectare was 149.7 t, 121.8 t, and 83.5 t for very dense forest, moderately dense forest, and open forest, respectively. Himalayan Moist Temperate Forests (part of the re-grouped 'Montane Moist Temperate Forest' in this study) constitute the highest percentage of forest cover in the state (36.7%) and have a carbon stock of 132.6 t/ha; the Himalayan Dry Temperate Forests and Sub-Alpine Forests (re-grouped as 'Sub-Alpine and Dry Temperate Forests' in this study) constitute 6.0% of the state's forest cover and have a carbon stock of 153.3 t/ha. The national average for these two forest types (re-grouped) is 127.2 t/ha and 119.2 t/ha, respectively (FSI 2012b).

Overall

Although the national average for forest carbon stock was 98.4 t/ha, it was 128.98 t/ha for the five states that mainly lie within the Himalayan region, and higher than the national average in almost all the canopy density strata, except in the moderately dense forest and open forest in Sikkim, where per hectare carbon stock was slightly less than the national average, and in the very dense forest in Uttarakhand, where per hectare carbon stock was about 11% less than the national average.

Conclusion and Future Plans

There are many forest initiatives at different stages from planning to implementation. All these initiatives have the objective of improving forest health for ecosystem services, biodiversity, climate change mitigation, and other reasons. The outcomes of these initiatives need to be

monitored quite regularly. Although the present methodology is statistically very sound as it is based on two-stage sampling, the first stage sampling units, i.e., the districts, are only covered in a cycle of 20 years, which is quite long. For national objectives, and the requirement of REDD+ and other international commitments, the country needs to refine its methodology, and at the same time capture regional variations more precisely, and to intensify the efforts.

At present, FSI is conducting a pilot survey to improve the NFI and is planning to switch from two-stage stratified sampling to completely systematic sampling by creating square grids of 5 x 5 km over the entire country. A cycle of five years is envisaged for forest inventory, and ten years for the 'trees outside forest' inventory. The new approach will certainly capture regional variations more precisely. The present methodology uses green wash as shown in the topographic sheets as a sampling frame, whereas the new methodology is envisaged to use the latest forest cover maps prepared by FSI so that the remote sensing data have a direct correspondence with the inventory field data. FSI has been using single square plots for field measurements for a long time; the new methodology envisages a cluster of circular plots. Inclusion of new variables is also contemplated so that newer parameters can be estimated more appropriately, e.g., standing dead wood, effect of insects and pests, water sources, important non-wood forest products, and damaging invasive species, among others.

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Understanding the Institutional Setup and Policies in the Context of Pakistan's REDD+ Programme

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There is a serious threat of accelerated deforestation and forest degradation in many parts of Pakistan in light of the rising population and associated demand for wood, weak governance of tenure, encroachment, and land cover change, compounded by the adverse impacts of climate change. The Government of Pakistan is promoting a REDD+ (Reduction of Emissions from Deforestation and Degradation) programme for preservation of forests through private sector led carbon sequestration and carbon credit generation. Pakistan started REDD+ initiatives in 2010 in an effort to create a financial value for the carbon stored in forests and offer incentives for forest dependent communities to reduce emissions from forest land. This paper provides an overview of the implementation status of national REDD+ initiatives in Pakistan, with a focus on the institutional setup, policies, and relevant challenges for implementation of the REDD+ programme. It is based on the outcomes of a consultation process for the development of a REDD+ road map for Pakistan, and a review of the available literature in books, reports, and research articles. Institutional and policy initiatives have been taken to encourage the private sector to allocate resources for REDD+ development in the country. However, a clear regulatory process still needs to be developed – urgently – to oversee REDD+ activities in the country, especially to ensure the rights of forestry stakeholders and indigenous people.

Keywords: Pakistan's REDD+, institutional setup, policies, drivers of deforestation, land tenure, capacity challenges

Introduction

Pakistan is comparatively poor in vegetation growth, and the forests are mostly limited to its northern areas in the administrative units of Khyber Pakhtunkhwa (KP), Gilgit-Baltistan (GB), and Azad Jammu & Kashmir (AJK). These mountain regions have natural limitations to the spread of forest cover due to the high elevation, large areas under snow cover, steep peaks, glaciers, low rainfall, extreme climate, and precipitous slopes. Most of these areas are limited in fulfilling the requirements for timber and fuelwood, and the local communities have a centuries old tradition of planting forest trees on farmland to supplement their timber,

fuelwood, and forage needs. Plantations on farm and barren land have increased many times over the last three decades. The natural forests are generally found on hill slopes at elevations from 1,500 m (5,000 feet) to 4,000 m (13,000 feet) (Rao and Marwat 2003). In some areas of Gilgit-Baltistan (Diamer District), local communities own almost all the forests, which are officially designated as 'private forest' (Private Forest Regulation 1975). Pakistan joined the UN REDD programme in 2010 to support the global effort to protect and enhance forestry resources for a better and low carbon future, and to ensure the social, economic, and ecological wellbeing of its people. Pakistan has since initiated REDD+ activities, however, the success of REDD+ implementation in Pakistan will depend on sound and effective policies and consistency with the relevant international agreements and guidelines.

This review paper aims to give an overview of the national implementation status of REDD+ initiatives in Pakistan. The focus is on the institutional setup and policies and relevant challenges for implementation of the REDD+ programme. The paper is based on the outcomes of a consultation process for the development of a REDD+ road map for Pakistan and a review of the available literature in books, reports, and research articles.

Forests and Forest Change in Pakistan

Pakistan is progressing towards protection and conservation of its limited and diminishing forests, which cover only 5.1% of the country's land area (4.34 million hectares) (FAO 2006). The target is to increase the area to 6% and bring an additional 1 million hectares of land under forest by 2015 (both natural forests and plantations spread throughout the country) in order to meet the Millennium Development Goals (FAO 2009).

Despite the limited area, the forests of Pakistan represent a range of different types based on the climatic variations within the country. These climatic variations divide Pakistan into nine distinct ecological zones and support the growth of different tree species in different climatic regions with forest types including Littoral and Swamp Forests (mangroves), Arid Sub-Tropical Forests, Dry Sclerophylous and Dry Deciduous Forests, Tropical Thorn Forests, Sub-Tropical Pine Forests, Moist Temperate Forests, Dry Temperate Forests, and Steppe Forests, and related areas including Alpine Dry Steppe, Sub-Alpine Scrub, and Alpine Meadows (Khan and Akbar 2005). Most of these forests are naturally regenerated; almost 80% are located in the northern highland watersheds of Khyber Pakhtunkhwa, Gilgit-Baltistan, and Azad Jammu & Kashmir, while the remaining 20% are mostly plantation forests including irrigated plantation, farm plantation, linear plantation, and roadside and railway plantation, as well as mangrove forests in the coastal areas of Karachi and Balochistan. The growing stock of wood in these forests is 160 million cubic metres per year (coniferous 138 million cubic metres and broadleaved 22 million cubic metres), with an average growing stock of 95 million cubic metres per hectrare per year (FAO 2010).Unfortunately, the socio-ecological status of Pakistan's forests is declining because of massive forest degradation and deforestation over the past few decades. The forests were destroyed at an alarming rate of 42,000 ha per year from 1990 to 2010, the second highest deforestation rate in the world (FAO 2010). The

alarming trends in the extent of Pakistan's forests over the last two decades can be seen from the figures given in Table 5. According to a recent study (Qamer et al. 2010), an overall decrease has been noticed in almost all the forest cover and vegetation classes in selected Hindu Kush Himalayan (HKH) regions in Pakistan. Over one decade, dense coniferous, sparse coniferous, and mixed coniferous broadleaf forests were degraded by 16,000 ha (1.75%), 175 ha (0.02%), and 56,950 ha (7.68%), respectively. However, there was an increase of 1.09% in the mixed class of broadleaf, scrub, and shrubs.

Table 5: **Changes in extent of forest cover in Pakistan, 1990–2010 (FAO 2010)**

Annual change rate (area in '000 ha)					
1990–2000		2000–2005		2005–2010	
ha/year	%	ha/year	%	ha/year	%
- 41,000 ha	-1.76	- 43,000 ha	- 2.11	- 43,000 ha	- 2.37

CO_2 emissions due to land use change and other woody biomass

According to the Global Forest Resources Assessment of the FAO (FAO 2010), Pakistan's forests contain 213 million tonnes of carbon in their living biomass. CO_2 emissions in the country due to land use change and other woody biomass stock in 1989/90 were given as 9,830 Gigagram (Gg) of CO_2 equivalent, while the cumulative CO_2 that could be reduced by mitigation options such as forest plantation on agricultural lands, agroforestry, and forest protection in coniferous forests could be as high as 877, 1,153, and 1,226 million tonnes of CO_2, respectively (REDD+ RPP 2013). The potential for enhancing carbon stock through afforestation and reforestation on degraded lands and sustainable forest management is high. The estimated total emissions in Pakistan from all five categories of emissions under REDD+ (deforestation and forest degradation, conservation, sustainable forest management, and enhancement of forest carbon stocks), and thus the potential for reducing emissions, ranges from 300 to 400 million tonnes CO_2 equivalent from 2012–2022 (OIGF 2011). All these figures need to be verified by more detailed analysis, which will require good coordination between the departments holding the relevant data.

The drivers of deforestation and forest degradation

The causes of deforestation and forest degradation in Pakistan include illegal logging, mostly for fuelwood, fodder, and timber; population pressure; and lack of land use planning; combined with intensification of agriculture, extension of housing colonies, settlements, and industry, landslides and erosion, salinity and waterlogging, droughts and floods, pests and disease, overgrazing and livestock pressure, migration, construction of roads and other physical infrastructure, mining, forest fires, poverty and lack of livelihood activities, lack of proper harvesting and transportation techniques in mountainous areas, and invasive species in dry areas like eucalyptus, mesquite, paper mulberry, and lantana. There are three categories of direct drivers: demand and consumption of products, land use change, and

natural or manmade hazards. Demand and consumption of forest products seems to be the most severe and critical, followed by land use change, and natural and manmade hazards. Among the most prominent drivers of deforestation and forest degradation are the low supply and high demand for fuelwood and timber (Figure 9) due to the increase in population (Table 6). The annual wood consumption in 2003 was 43.76 million cubic metres, while annual forest growth was 14.4 million cubic metres, a supply gap of 29.34 million cubic metres (FAO 2006) resulting in high pressure and overexploitation of the limited forest resources. Currently, the availability of forest in Pakistan is an average of 0.3 ha per capita, only half the 0.6 ha per capita available at global level (FAO 2010).

Figure 9: **Historic and projected consumption of wood in Pakistan 1993–2018 (m³)**
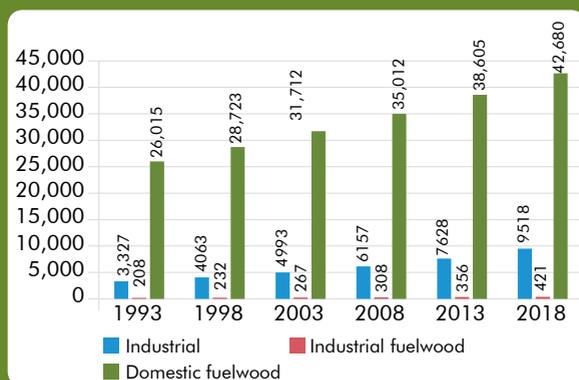
Source: FAO 2009

Table 6: **Population statistics for Pakistan, 2008**

Pakistan population 2008				
Country area ('000 ha)	Total ('000)	Density pop/ km²	Annual growth rate (%)	Rural population (% of total)
7,708	176,952	230	2.2	64

Source: FAO 2010

Agricultural expansion is also a severe problem in all forest types except mangroves, where agriculture is not possible. Climate change is a potential future driver; it is the main cause of changes in the occurrence and severity of floods, drought, disease, and forest fire, while mangrove forests may be affected by sea level rise. The indirect drivers of deforestation and forest degradation can be broadly divided into four categories: social, political, legal, and economic and resource management. Lack of alternatives, poverty, lack of awareness, shortage of energy, and political influence are the most critical indirect drivers of deforestation and forest degradation. Lack of resources, unemployment, weak governance and policies, urbanization, and unwise use of timber and fuelwood have been identified as the second most critical drivers. The majority of households continue to use fuelwood for cooking and heating. More than 50% of domestic energy needs are met through fuelwood. Fuelwood consumption in 1990 was estimated at 25.95 million cubic metres, rising to 31.52 million cubic metres in 2000, of which 90% came from farmland and the rest from state forests (REDD+ RPP 2013). However, deforestation is not only the result of commercial logging and wood harvesting by

Figure 10: Projected changes in forest cover in Pakistan 1992–2020 (million ha)

	2003	2010	2015	2020
Coniferous forest	1,233	1,033	892	632
Scrub forest	1.521	1.587	1.652	1.719
Riverain forest	158	156	154	152
Mangrove forest	125	101	77	52
Irrigated plantation	194	214	234	254
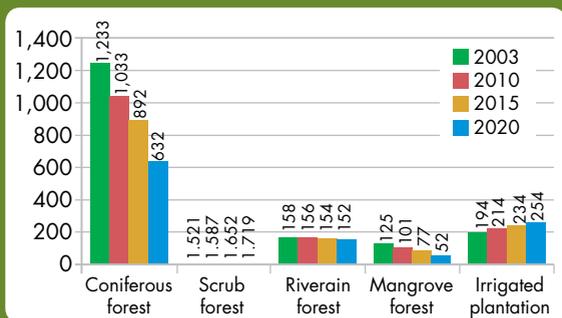
Source: FAO 2009

the poor. Indeed, poor communities have become increasingly disempowered in managing forest resources as their rights to forests have weakened due to economic pressure from commercial loggers. Illegal and excessive tree cutting has resulted in severe soil erosion, flood damage, desertification, and land degradation in many areas. Removal of trees leaves the soil exposed and less able to absorb rainfall. Excess water runs off and causes soil erosion, speeding-up the process of denudation and eventually leading to desertification.

The removal of top soil is also resulting in low production of forage, fodder, fuelwood, timber, cereal crops, and grain, which is exacerbating poverty in rural areas. Removal of vegetative cover from steep slopes also contributes to flash floods and increases the sedimentation load in rivers. About 11 million hectares of the northern mountain regions are affected by water erosion, bringing about 40 million tonnes of sediment into the Indus water basin every year. This reduces land productivity, shortens the lifespan of major upstream reservoirs like the Tarbela and Mangla, and reduces the efficiency of hydropower generation and irrigation systems downstream. The projected change in forest cover in Pakistan due to the above drivers is shown in Figure 10.

Land tenure and rights

According to data from 2005, 66% of the ownership and management rights of forest rests with the public, while 34% is under private ownership and management (FAO 2010). From the tenure point of view, there are two main categories of forest: state owned and private. State owned forest land is legally classified into five classes: state, reserved, protected, un-classed, and resumed lands. Private forest land is classified into Guzara forest, communal forest, Section 38 areas, and Chos Act areas. In addition to forest, there are vast areas of range and pasture lands from the coastal zone to alpine areas with seven major range types: grassland, grass-woodland, grass-shrubland, grass-forb land, woodland, shrubland, and forb land. Legal protection of forests is provided under the Forest Act (1927), and associated rules and regulations, amended from time to time as necessary. The common land tenure system prevailing in Pakistan is of private landlordism. Here individuals are the owners of the land. They pay revenue under periodical settlements. The holdings under this system vary considerably in size, ranging from 0.5 ha of land to hundreds or thousands of hectares. The big landlords retain some land for their own cultivation, while the major share is parcelled out in small lots to tenants. There are two types of tenants: occupancy tenants, i.e. tenants who enjoy considerable security of tenure because they have been cultivating the land since the

time of their forefathers; and tenants-at-will, i.e. tenants who can be ejected at any time by the landlord and have no security of tenure. Landless rural labour is composed of persons living mainly from the land, but with no direct tenure of land. Their relation to land is indirect: they provide their labour to landowners and cultivators against a share of the produce. Absentee landlords and their tenants do not consider afforestation or sustainable use of land resources. Therefore, a comprehensive study on land tenure and natural resource rights is required to be conducted to support the effectiveness of policy decisions.

REDD+ Trajectory in Pakistan

REDD+ and the 18th amendment in the Constitution of Pakistan

Following the18th amendment to the constitution of Pakistan, some 44 topics, including pollution, ecology, and the environment, became the sole legislative domain of the provincial assemblies. All institutions, regulatory bodies, resources, staff, and liabilities related to the environment have been transferred to the administrative units (provinces and others), except for those having jurisdiction in the Federal Capital Territory. Under the Constitution of Pakistan, forestry is a provincial matter and provincial governments formulate their own strategies and action plans to achieve the goals and objectives of the policy on forests. The federal government under its mandated functions coordinates and facilitates the provinces through national policy, programmes, and projects. International agreements, including the UNFCCC and its REDD+ mechanism, fall in the domain of federal functions, therefore, the Office of the Inspector General of Forests (IGF) was designated as the National REDD+ Focal Point for Pakistan in 2010. However, the potential challenge that may emerge as Pakistan moves ahead with REDD+ is that under the 18th constitutional amendment, environment has been removed from the concurrent list. Some provinces have shown a trend of entering into direct agreements with private companies for pilot REDD+ projects. The Office of the Inspector General of Forests (OIGF) has been building inter-provincial coordination and inter-institutional linkages on REDD+ implementation, and has taken the initiative to discuss initiation of the process of REDD+ in Pakistan with the provincial forest departments. Devolution of the Environment Ministry leads to greater challenges, especially in its role and distribution. Devolution is a constitutional requirement, but international conventions require national entities to take ownership and distribute these functions rationally and responsibly. Equally, the national obligations taken up by countries, including Pakistan, require oversight, monitoring, and reporting at the national level and not just provincial or local. The text of the Cancun and Durban Agreements on REDD+ is clear about national forest carbon accounting and national emissions; however, these matters have already been conveyed to the provinces. The consultations held in the past three years with the provinces have created high hopes that the challenge to taking up REDD+ at the national level created by the 18th constitutional amendment will be resolved with the provinces in accordance with the UNFCCC REDD+ related agreements. The administrative units have recently started acting on the advice of the national focal point for REDD+ and there is a trend towards all REDD+ related initiatives in the provinces being shared with the national focal point.

Institutional setup for REDD+ implementation

Despite the fact that Pakistan is a member of the Coalition of Rain Forest Nations, the group that started the REDD+ debate, and was a signatory to the initial REDD+ proposal submitted by 23 countries from the Rain Forest Coalition through the Ad Hoc Working Group on Long Term Cooperative Actions (AWG-LCA) (2008), the country has unfortunately been a little late in joining the global efforts under REDD+. Pakistan started REDD+ initiatives in 2010. A National REDD+ Steering Committee was also established in 2010, and provincial REDD+ focal points were designated from the respective forest departments. Pakistan also developed a voluntary REDD+ database (VRD) and joined the REDD+ Partnership that was formed in Oslo in May 2010 that serves as an interim platform for partner countries to scale up actions and finance for REDD+ initiatives. Pakistan joined UN-REDD as a partner in 2011 and is set to operationalize and mainstream REDD+ in its forest management practices. In July 2013, Pakistan also became a member of the Forest Carbon Partnership Facility (FCPF) and submitted a REDD+ Readiness Preparation Proposal (RPP) to the FCPF. This was approved, and Pakistan secured USD 3.4 million for the next five years. Pakistan also succeeded in securing funds through a Global Environment Facility (GEF) allocation of USD 10 million under the Clean Development Mechanism and Climate Change, which also addresses REDD+ (Khan and Nasir 2011).

A project for the REDD+ preparedness phase in Pakistan has been initiated by the Ministry of Climate Change of the Government of Pakistan with financial assistance from the United Nations Development Programme (UNDP) through One UN Joint Program on Environment (JPE), which allocated USD 0.2 million. The project proposal was developed by the International Centre for Integrated Mountain Development (ICIMOD); ICIMOD and the World Wide Fund for Nature Pakistan (WWF-P) are the implementing partners. The project had three main aims: 1) capacity building, 2) development of a road map for preparing a national REDD+ strategy, and 3) developing a national REDD+ project proposal to enable the Ministry of Climate Change to seek additional funding for the REDD+ process. ICIMOD provided technical assistance to the Government of Pakistan in implementing the project. A series of consultative workshops were organized in 2013 under the project jointly by the implementing partners in all provinces. The workshops were organized for communities and other stakeholders (local forest community members, forest contractors, local NGOs, academia, media personnel, and officials from various government departments) to identify the drivers of deforestation and forest degradation in their respective areas through their valuable feedback. During the third week of November 2012, the UN-REDD mission for Asia and Pacific also visited Pakistan for the first time on the invitation of the national REDD+ focal point at the Ministry of Climate Change and held several meetings with REDD+ implementing partners in the country. The output of these meetings was a proposal that was developed to extend UN-REDD technical and financial support to the current REDD+ project initiatives in Pakistan. The REDD+ initiatives are currently at preparedness phase, in a joint initiative by the Ministry of Climate Change, FAO, ICIMOD, One UN Joint Program on Environment, and WWF-Pakistan. In 2013, Provincial REDD+ Management Committees were formed in Punjab,
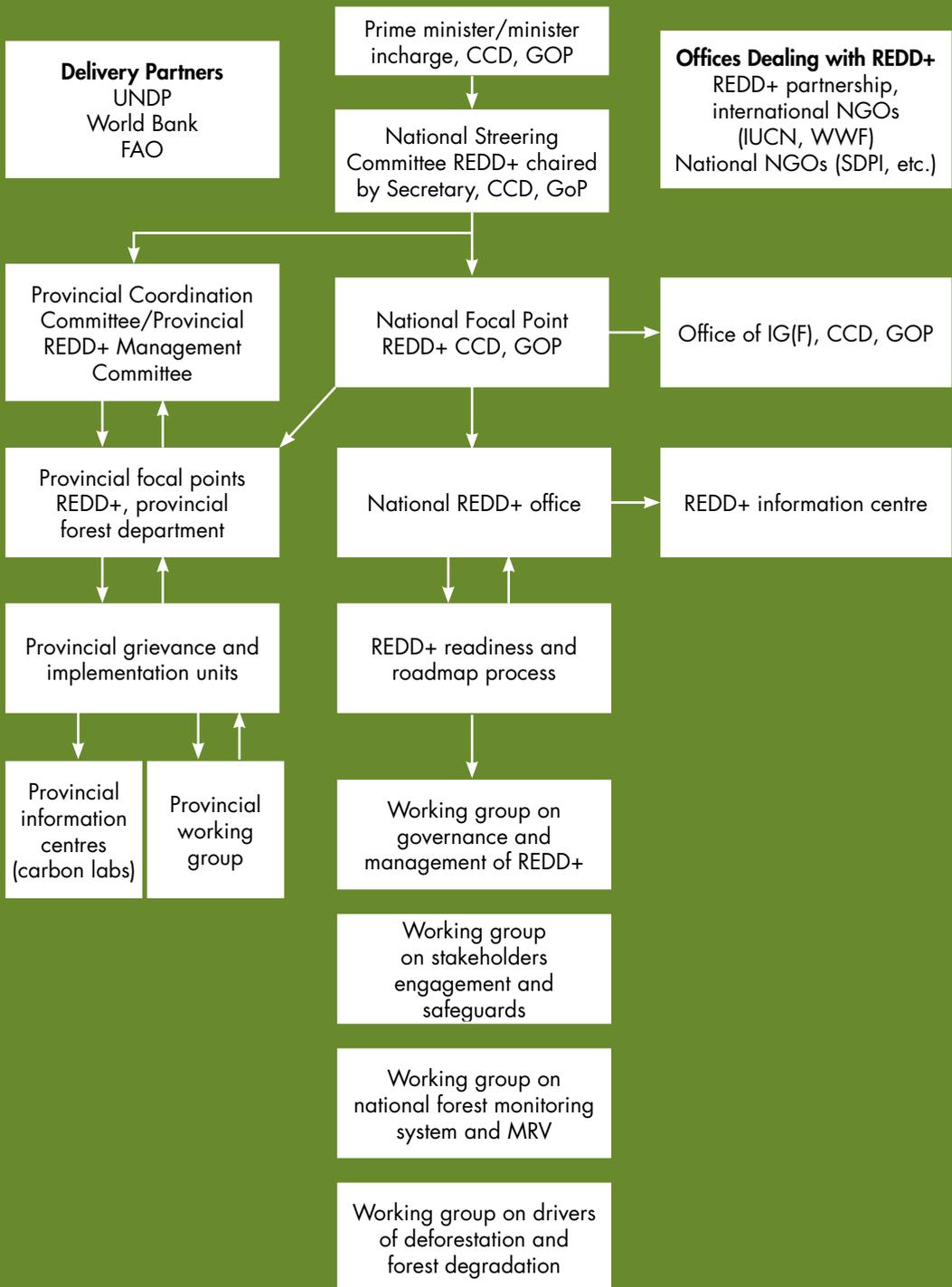
Sindh, Khyber Pakhtunkhwa, Gilgit-Baltistan, and Azad Jammu & Kashmir (AJK), and four working groups were formed on governance and management of REDD+; stakeholder engagement and safeguards; national forest monitoring system and MRV; and drivers of deforestation and forest degradation. The national institutional setup proposed in the REDD+ Readiness Preparation Proposal submitted to FCPF is shown in Figure 11.

Key policies, laws, strategies, and programmes relevant to REDD+

The REDD+ initiatives were started with the inclusion of REDD+ in the National Climate Change Policy of Pakistan (NCCP), which has now been approved, followed by the development of a Project Investment Fund (PIF) by the then Ministry of Natural Disaster Management (now Ministry of Climate Change) for tapping a GEF grant under REDD+ or sustainable forest management (SFM). REDD+ forms an important component of the NCCP as a mitigation measure; under the policy measures the NCCP clearly spells out 'secure financial assistance' from the World Bank's FCPF and UN-REDD Programme, as well as from other international sources, to formulate a national programme for avoiding deforestation and forest degradation. The National Forest Policy has a similar provision for mainstreaming REDD+ as a tool to curb deforestation and enhance forest cover and forest carbon stocks. All provinces have prepared drafts for provincial forest policies. The provincial forest policies of Punjab and Khyber Pakhtunkhwa have been approved by their respective provincial cabinets. However, none of the policy initiatives, or the policy itself, can be successful or effective without a legal basis with supporting laws. The Khyber Pakhtunkhwa Forest Ordinance, which was promulgated in 2002, defines the institutional details for forestry in the province, following the guidelines given by the Provincial Forest Policy 2001. The public forests in Gilgit-Baltistan, Punjab, Sindh, and ICT are managed under the Forest Act 1927; in Balochistan under the Balochistan Forest Regulations 1890 (amended 1974) as well as the Forest Act 1927; while in AJK they are managed under the Jammu & Kashmir Forest Regulations 2 of 1930. Other laws relevant to REDD+ include the Provincial Wildlife Acts and Ordinances like Balochistan Wildlife Protection Act 1974, and Pakistan Environmental Protection Act 1997. Issues like forestry, REDD+, and climate change are not detailed in the provincial local government acts. Only the protection of trees and wildlife is mentioned in a very broad manner. REDD+, carbon trade, or the resulting access and benefit sharing mechanism, are not mentioned at all under the existing laws. However, such issues are being included in the revised acts. As in other provinces the Forest and Wildlife Department of the Government of Balochistan is in the process of revising various Acts. The Balochistan Forest Act 2013 and Balochistan Wildlife, Biodiversity and Protected Areas Act 2013 are being revised and are in the process of being submitted to the cabinet, after which they will be submitted to the provincial assembly. The Gilgit-Baltistan Forest Department has developed its first draft Forest Policy (2015) and is also revising all other relevant policies, laws, regulations and acts to include REDD+ and other important provisions under global scenarios.

The main strategies and action plans relevant to REDD+ include the National Conservation Strategy, National Sustainable Development Strategy (draft), Biodiversity Action Plan, and

Figure 11: **National REDD+ institutional arrangements**


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                        Prime minister/minister
                        incharge, CCD, GOP
Delivery Partners                                      Offices Dealing with REDD+
UNDP                                                   REDD+ partnership,
World Bank                                             international NGOs
FAO                      National Streering            (IUCN, WWF)
                         Committee REDD+ chaired       National NGOs (SDPI, etc.)
                         by Secretary, CCD, GoP

Provincial Coordination
Committee/Provincial     National Focal Point          Office of IG(F), CCD, GOP
REDD+ Management         REDD+ CCD, GOP
Committee

Provincial focal points
REDD+, provincial        National REDD+ office         REDD+ information centre
forest department

Provincial grievance and REDD+ readiness and
implementation units     roadmap process

Provincial    Provincial Working group on
information    working   governance and
centres        group     management of REDD+
(carbon labs)
                         Working group
                         on stakeholders
                         engagement and
                         safeguards

                         Working group on
                         national forest monitoring
                         system and MRV

                         Working group on drivers
                         of deforestation and
                         forest degradation
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Source: REDD+ RPP (2013)

Forestry Sector Master Plan (MOE 1992). Programmes and projects like the Sustainable Land Management Programme and Mountain and Market: Biodiversity and Business in Northern Pakistan are relevant to REDD+; they will provide opportunities to reach out to grassroots communities to undertake afforestation and protection of forests. Resource management instruments and tools relevant to REDD+ include traditional forest working plans; revised and improved management plans; specialized forestry programmes and projects such as watershed management, social forestry, and farm forestry; the joint forest management system; community-based forest management system; and local traditional management systems such as the Nagha and Aman systems.

Challenges to set institutional policies

Provincial forest policies traditionally placed greater emphasis on maintaining government control and the enforcement of edicts than on the needs of the communities who lived in and around forests. As a result, existing community rights to forest resources became proscribed. The policies resulted in a small, well-preserved public forest estate, but provided nothing for improving and extending forests. It also lacked participation of forest communities. The top down, non-participatory approach drove a wedge between communities and their birthright by denying them a say in its management and subjecting them to legal process, which was often arbitrary. The unprecedented levels of degradation that the country is currently witnessing, partly has its roots in this. Provincial forest policies lack measures to encourage communities to carry out afforestation. Many critical issues in deforestation and forest degradation, such as illegal logging, encroachment, and conversion of forest land to non-forest uses, are due to the absence of land use plans and a defined policy of the government to this affect. Moreover, despite several attempts, the draft National Forest Policy is still awaiting approval by the cabinet. Until recently, most forest policies have viewed people as the prime threat to the forests, and have attempted to exclude groups other than the government from decision making. This approach has not only affected the sustainability of the livelihood strategies of the local people, but also increased the vulnerability of the marginalized sections of communities, and ultimately led to the unsustainable management of natural resources and forest depletion. The Forest Ordinance of Khyber Pakhtunkhwa, for example, is punitive and tends to increase the policing role of forest departments. For example, the Forest Ordinance designates forest department staff to be a uniformed force bearing arms, and also enhances their police powers, which goes against the intent of the Provincial Forest Policy that enshrines the principles of participatory social forestry. Similarly, the discretionary powers of forest officers to revoke a community-based organization (CBO) or joint forest management committee (JFMC) agreement, as suggested in this ordinance, would result in uncertainty and insecurity among different JFMCs and CBOs.

Way forward

The most important issue is the lack of the technical capacity and skills required for successful implementation of REDD+ in Pakistan. Institutional capabilities do exist, but their

understanding and capacity regarding technical aspects of REDD+ (e.g. satellite land monitoring system to assess activity data on forest area and forest area changes, and national forest inventory to assess emission factors on carbon stocks and carbon stock changes) need to be enhanced and strengthened. Provincial capacity building and training units under provincial REDD+ cells have been proposed in the REDD+ RPP, which mostly focuses on the capacity issues. Khyber Pakhtunkhwa and Gilgit-Baltistan have recently trained their focal points in advanced terrestrial carbon accounting for REDD+. The trained focal points are being used as master trainers to further build the capacity in other provinces. The national MRV strategy and action plan is also under development, for which both international and national expertise will be utilized through a consultative process. Pakistan has also recently developed and submitted, through an intensive consultative process at both national and provincial level, its REDD+ Readiness Preparation Proposal for a potential financial grant from the Readiness Fund of the World Bank Forest Carbon Partnership Facility. The following REDD+ strategy and governance options have been conceived for Pakistan:

- A market/project based architecture including buyers and sellers of carbon stored in forests. Buyers are firms with emissions reduction responsibilities. Sellers are owners of forests or actors with use rights to forest resources. Interaction between these will take the form of trade.
- A system with national REDD+ funds outside the national administration including the establishment of a national fund, with a non-commercial actor as an intermediary between forest owners/users and potential financers of REDD+ activities. The board may contain representatives from the private sector, civil society, and public authorities. These may have the capacity to support programmes in cooperation with local communities.
- A national REDD+ fund organized under the national administration that utilizes the capacities and competencies of present state administrations. However, allocation is made by a separate board with REDD+ responsibilities only. This is set up independent of the ordinary budgetary process with a specified responsibility to allocate funds to REDD+. It reports to the government but may also include representatives from civil society and the business sector. It may be institutionalized to use the capacity of the state administration to command, but may also be involved in direct trade with forest owners and users.
- Conditional budget support utilizing existing state structures. Resources flow from an international fund to the respective state on the condition of fulfilment of REDD+ activities. Resources are allocated to various activities/forest owners/users relying foremost on the command power of the state.

At present, a project titled 'Preparation of action plan and capacity building for a national forest monitoring system (NFMS) for REDD+' is being implemented by WWF-Pakistan under the overall supervision and guidance of the OIGF to take the REDD+ preparation further and help Pakistan develop a robust national forest monitoring system. The UN-REDD Programme is providing both financial and technical support under its Target Support Fund. The project has two outputs: 1) development of the NFMS action plan; and 2) development of the capacity of stakeholders for forest monitoring, greenhouse gas inventory, and overall implementation of the NFMS action plan. Under Output 1, the project intends to 1) conduct detailed mapping of existing NFMS capacity, gaps, and needs of both national and provincial

forest administrations and other relevant government organizations, 2) develop a standard methodology for spatial analysis of forest cover change, 3) assess data availability for LULUCF (land use, land use change, and forestry) GHG inventory, and 4) develop a draft NFMS action plan. In this connection, WWF-Pakistan and the OIGF, in coordination with FAO, conducted an inception workshop on the 'Preparation of an Action Plan and Capacity Building for a National Forest Monitoring System for REDD+' in March 2014 for orientation of key national and provincial stakeholders in REDD+, and development of an action plan. A formal report on the proceedings of the workshop was submitted to the OIGF on 27 May 2014. The WWF-Pakistan team, in consultation with OIGF, hired a national consultant for the project in May 2014 and engaged him to accomplish the outputs of the project. According to the work plan, the national consultant has conducted a thorough assessment of the existing NFMS and MRV systems in place in all provinces including Gilgit-Baltistan, AJK, and Federally Administered Tribal Areas, and submitted a final capacity based needs assessment (CBNA) report to the OIGF in December 2014. Based on the CBNA report, the NFMS action plan is being drafted; it is expected to be completed in May 2015.

Conclusion

A REDD+ process was initiated by the Government of Pakistan in 2009 with consultative workshops and awareness raising. In 2012, a multi-stakeholder steering committee, provincial coordination, and REDD+ management committees were constituted. National and provincial focal points were declared. Working groups were formulated to compile and deliver information on the following: 1) governance and management of REDD+; 2) stakeholders' engagement and safeguards; 3) national forest monitoring system and MRV; and 4) drivers of deforestation and forest degradation. All the relevant bodies are working together to create awareness and undertake the necessary preparation for the REDD+ readiness process in Pakistan. The inputs acquired through this process are being utilized to develop the REDD+ national strategy and implementation plan. The consultation activities have produced several important outcomes, including identification of a range of stakeholders relevant to REDD+ along with the outreach methods that enhanced both collaboration and capacity building among national, provincial, and local level line agencies and other respective organizations, and hence enhanced ownership of the REDD+ mechanism. During the consultation process, various capacity building needs were also identified. At present a project on 'preparation of action plan and capacity building for a national forest monitoring system for REDD+' is being implemented.

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Status of the Forest Cover Assessment and Monitoring System in Pakistan in the Context of REDD+

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*F*orests are both a carbon sink and a source of greenhouse gas emissions. Reducing Emissions from Deforestation and Forest Degradation (REDD+) has been introduced by the UNFCCC as a strategy to reduce GHG emissions and sustain forests. Pakistan is suffering from high deforestation rates and has joined the UN-REDD programme. Assessment of forest cover and change is an essential part of the REDD+ approach. This study looks at the status of the forest cover assessment and monitoring systems in Pakistan. The majority of studies are based on remote sensing, which is considered to be the most reliable method for monitoring under the current scenario. However, the reported values for forest cover vary considerably, which may be the result of both the different methodologies used and different classification criteria for forest. Notwithstanding these differences, the assessments indicate that Pakistan's forests are undergoing extensive removal and degradation. Monitoring, reporting, and verification (MRV) is coupled to REDD+ in order to establish a baseline monitoring system and to provide a standardized approach for systematizing the assessment. The existing data do not yet provide a reliable baseline, and Pakistan is in the process of developing an appropriate system.

Keywords: REDD+, forest cover, remote sensing, monitoring, Pakistan

Introduction

Forests are a major carbon sink and absorb one-third of anthropogenic carbon emissions. At the same time, deforestation and degradation contribute almost 17% to the global anthropogenic greenhouse gas (GHG) emissions (IPCC 2007). Reducing Emissions from Deforestation and Forest Degradation, Conservation of Forest Carbon Stocks, Sustainable Management of Forests, and Enhancement of Forest Carbon Stocks (REDD+) is a strategy to reduce GHG emissions and sustain forests. The UNFCCC plans to use the REDD+ mechanism to make economic support available not only for reducing deforestation rates, but also for conserving or increasing existing forest carbon stocks using sustainable forest management. The approach provides a basis for financial benefit by generating carbon credits. REDD+, with a primary focus on tropical forests, has been implemented successfully in various parts of world.

Pakistan is suffering from high deforestation rates which are estimated to have reduced forest cover from 5 to 2.5% (FAO 2010). The country joined the UN-REDD Programme in 2011 and has received Targeted Support funds to develop a REDD+ Readiness Roadmap (UN-REDD nd). Pakistan is also a signatory to the United Nations Framework Convention on Climate Change (UNFCCC) and is one of the Non-Annex 1 parties to the Convention; the Pakistan Government endorses the principle of "common but differentiated responsibilities" put forward by the convention as a basic prerequisite. Pakistan is forest-poor, mainly due to the arid and semi-arid climate in large parts of the country. The main types of forest in the less arid parts are juniper, chilghoza, scrub, riverine, and mangrove. Most of the forest area is in the northern part of the country in Khyber Pakhtunkhwa (KPK) and Azad Jammu & Kashmir (AJK) provinces and comprises coniferous and scrub forest. Irrigated plantations have been raised mainly in Punjab and Sindh provinces. Different types of rangeland are also distributed throughout the country. The present study was carried out with the objective of reviewing existing land cover and forest cover mapping studies for Pakistan as background information for developing a forest assessment process suitable for natural resources management and REDD+. Several studies have been conducted by different agencies and experts using different data and methodologies and for different periods of time.

Forest Cover Assessment in Pakistan

Three major national studies of forest cover have been carried out in Pakistan using satellite images but with somewhat different methodologies: the Forestry Sector Master Plan (FSMP) study carried out in 1992, the National Forest and Range Resource Study (NFRRS) in 2003/4, and the Land Cover Atlas for Pakistan in 2012. In addition, the United Nations Food and Agriculture Organization (FAO) has published assessments of forest cover derived from national statistics, and ICIMOD has studied forest cover and changes over time in three northern provinces. The studies are summarized below.

The Forestry Sector Master Plan

The first comprehensive remote sensing based national land cover assessment was carried out under the Forestry Sector Master Plan (FSMP) in 1992 with the aim of estimating national forest cover disaggregated at province level. The forest resources assessment was based on manual interpretation of hard copies of Landsat TM images at 1:250,000 scale for 1989 and 1990 obtained from SUPARCO. The images were RGB products of Landsat TM bands 2, 5, and 7. The forest areas were identified and marked manually on the basis of differences in tone and texture, and broadly categorized into coniferous and broadleaved types. Small stands of forest and isolated trees could not be detected at the 30 m resolution of the Landsat TM. An independent field survey was conducted in all the provinces in Pakistan by Asianics Agro-Dev International, a private sector company, to assess the area of forest on farmland (small patches of trees and scattered trees on private land). FSMP gave the forest area as 3.59 million hectares – equivalent to 4.1% of the total land area of Pakistan (GOP 1992). Of this, 67% was in the three administrative units of Khyber Pakhtunkhwa (1.49 million hectares),

Gilgit-Baltistan (0.66 million hectares), and Azad Jammu & Kashmir (0.26 million hectares) in the Upper Indus basin. The Landsat TM based forest assessment under FSMP formed a strong basis for future planning and the statistics generated by the FSMP are still referred to as the benchmark.

The National Forest and Range Resource Study

Twelve years later, in 2003/04, the Ministry of the Environment conducted the National Forest and Range Resource Study (NFRRS) through the Pakistan Forest Institute (NFRRS 2004, PFI 2012). Landsat ETM+ images at 30 m resolution from 1997 and 2001 were digitally processed to provide an assessment of forest cover across the country. The PFI used supervised classification with a maximum likelihood classifier. A forest inventory plot system (FIPS) was established to facilitate statistically reliable and accurate assessment; forest and field investigations were carried out. The study reported a total forest area of 3.62 million hectares in 1997 and 3.32 million hectares in 2001.

The Land Cover Atlas for Pakistan

The relatively low resolution results of the FSMP and NFRRS provided concise baseline information for policy level awareness and decision making, but they did not provide the systematic baseline data disaggregated at the level of local administrative boundaries (e.g., district and tehsil) which is needed to accurately measure the current extent of forest cover and the deforestation rates in any particular district.

In 2012, PFI developed a land cover atlas (LCA) for Pakistan using digital processing of SPOT5 2.5 metre spatial resolution images acquired in 2007 under the Forestry Sector Research and Development Project (FSR&DP). The study aimed to 1) prepare an atlas of all districts in the country indicating the distribution of various natural resources; 2) to monitor forest change; and 3) to build the capacity of professionals in provincial forest departments in GIS and remote sensing techniques for natural resource management.

According to this atlas, the total forest area in Pakistan in 2007, excluding alpine pastures, farmland trees, and linear plantation, was 4.34 million hectares or 5.01% of the total area. Forest cover in KP was 1.51 million hectares (20.3%), Punjab 0.55 million hectares (4.6%), Sindh 0.66 million hectares (2.7%), Balochistan 0.50 million hectares (1.4%), Gilgit-Baltistan 0.34 million hectares (4.8%), AJK 0.44 million hectares (9%), Federally Administered Tribal Areas (FATA) and Frontier Regions 0.53 million hectares (19.5%), and Islamabad 0.22 million hectares (22.2 %) (PFI 2012).

The FAO assessment

FAO has published values for the total forest cover in Pakistan as part of its global forest assessment. The values were derived from estimates made by the Forest Department based on the FSMP data and various field measurements extrapolated on the basis of certain

assumptions FAO reported the area of forest cover in 1990, 2000, and 2010 to be 2.5, 2.1, and 1.7 million hectares (2.9%, 2.4%, and 2.0% of the total area) (FAO 2010). Similarly, World Bank reports refer to Pakistan's total forest cover as being 2.2% percent of the land area of the country (equivalent to 1.9 million hectares) (World Bank 2012). However, a different FAO assessment (FAO 2007) gave the value for the total area of forest in Pakistan as 4.34 million hectares (5.0%), of which 3.44 million hectares were state owned, and tree cover on farmlands and private forests was 0.78 million hectares (0.89%), based on the early results of the Land Cover Atlas.

Comparison of the studies

The characteristics of the three major studies are shown in Table 7; the results obtained by the different studies and reported by others are shown in Table 8.

Table 7: **Major national studies of forest cover in Pakistan**

Study	Satellite data used	Resolution	Year of acquisition	Interpretation method	Executing agency
Forestry Sector Master Plan (FSMP) 1992	Landsat TM	30 m	1989–1990	Visual interpretation of printed images at a scale of 1:250,000	Ministry of the Environment
National Forest and Range Resources Assessment Study (NFRRAS)	Landsat ETM	30 m	1997–2001	Supervised classification, forest inventory plots used to facilitate assessment	Pakistan Forest Institute
Land Cover Atlas of Pakistan	SPOT-5	2.5 m	2007	Visual interpretation	Pakistan Forest Institute

Table 8: **Values for Pakistan forest cover from different reports**

Study	Reference	Forest area (million ha)						
		1989/90	1997	1999	2000	2001	2007	2010
FSMP	GOP 1992	3.59						
NFRRS	NFRRS 2004		3.62			3.32		
LCA	PFI 2012						4.34[a]	
FAO	FAO 2010[b]	2.5			2.1			1.7 (3.14b)
World Bank	World Bank 2012							1.9[c]

[a] Excludes alpine pastures, farmland trees, linear plantation
[b] Excludes 'other wooded land'; in 2010 forest + other wooded land amounted to 3.14 million hectares
[c] Year not given

The extent of current forest cover and deforestation rates in Pakistan remains a matter of discussion. The different methodologies and definitions used in the various studies make any comparison or assessment of deforestation rates problematic. The PFI compared the NFRRS results with the FSMP results and reported that 270,000 ha of natural forest had been

removed (deforestation) since 1992, equivalent to 0.7% per annum over the decade (NFRRS 2004). However, direct comparison of the two results was not technically justifiable as the results were derived from widely different methodologies. The values reported in FAO's global forest assessment indicate a loss of 1.6% of forest cover per annum from 1990 to 2000 and 2.0% per annum from 2000 to 2010. But the total area of forest cover reported, although based on national statistics, is markedly lower than the values found by the three national surveys. FAO (2007) recorded that an average area of 31,658 ha (0.75%) of natural forest is removed annually, while the standing volume of farmland trees (plantation) was increasing at 3.9% per annum. The net loss of woodland and forest habitat from 1990 to 2005 was calculated to be 14.7%, or just under 1% per annum. Equally, the most recent national survey, which used high resolution satellite images, reported a total forest area that was higher than the area reported by the previous surveys.

The differences reported in total cover are likely to be mainly methodological, the studies that report change show that the extent of forest cover is being reduced, and ground observation also indicates that deforestation and forest degradation is proceeding at a noticeable rate. A similar situation has been observed in other global assessments with differing values for forest cover extent, which have been attributed at least in part to the lack of a clear definition of 'forest land' (Mather 2007). Only a few countries have reliable data from comparable assessments over time (FAO 2010); the lack of such data is a challenge for developing efficient forest management policies.

The ICIMOD study

Standardization in forest cover and land cover mapping is important for comparative assessment of the biosphere. There is a clear need for a comparative assessment of Pakistan's forest area carried out over time using a standardized methodology. The International Centre for Integrated Mountain Development (ICIMOD) is an independent intergovernmental organization with a regional mandate and supports countries in carrying out land cover classification at national level using the Land Cover Classification System (LCCS) developed by FAO/UNEP to facilitate assessment and management of natural resources. The LCCS is a comprehensive standardized classification system based software designed to meet specific user requirements and created for mapping exercises independent of scale or method. Using the standardized land cover classification, ICIMOD conducted time series land cover mapping of the mountain areas of Pakistan (specifically Gilgit-Baltistan, Khyber Pakhtunkhwa, and Azad Jammu & Kashmir). The aim was to assess past changes and present trends in land cover distribution, with a special emphasis on forest cover change. The specific objectives were to assess the current land cover distribution and analyse change over the last two decades, assess the district-wise deforestation patterns, devise a mechanism for regular monitoring of the forest resources, with a particular focus on a monitoring and verification system to report on REDD+, and to make this information and methodology available for both national level decision making and the international reporting requirement. The study used level-one-terrain corrected product (L1T) temporal Landsat data from USGS EROS (http://eros.usgs.gov/) from

Figure 12: **Deforestation hotspots based on the ICIMOD assessment**
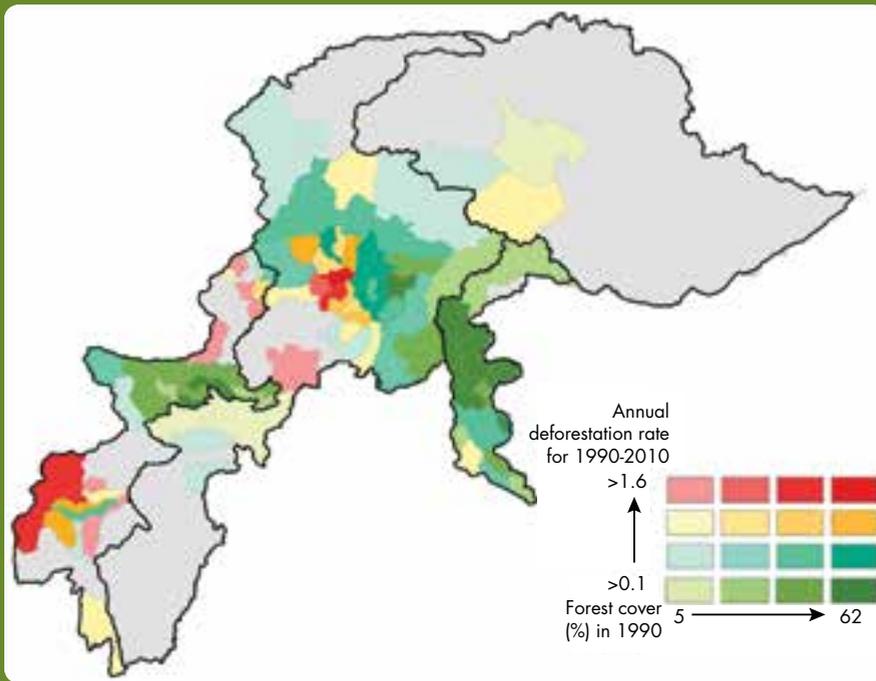
years close (±2) to 1990, 2000, and 2010. The results of the study produced time series forest cover change between 1990–2000–2010 disaggregated at sub-district level (Figure 12).

The overall and district level decadal land and forest cover data can be visualized through a web portal (http://apps.geoportal.icimod.org/PKLandcover/). The time series forest cover maps (1990–2000–2010) revealed extensive deforestation, with a loss of 161,556 ha of forest over 20 years, a rate of 0.36% per year (Figure 12). A further 43,922 ha had become severely degraded. The total forest cover for the three provinces of AJK, Gilgit-Baltistan, and KP in 1990 was 2.26 million hectares, close to the value of 2.41 reported by the FSMP, while that in 2010 was 2.10 million hectares, close to the value of 2.29 reported in the Land Cover Atlas.

Forest Stock in Pakistan

It is extremely difficult to calculate the biomass of the forest stock in Pakistan accurately without consistent data for forest cover or detailed analysis in terms of forest types and forest density. However, some assessments have been made by FAO in the Global Forest Assessment Report based on the limited information available as described in the following (FAO 2010).

National biomass stock

Biomass is usually categorized into three main classes: above ground biomass, below ground biomass, and dead wood. Table 9 shows the biomass variables in Pakistan's forests over time. The weighted biomass density was taken to be 0.7, as given in the Forest Sector Master Plan 1992. The biomass expansion factor was calculated using the Sandra Brown formula [BEF = EXP (3.213-0.506*LN (biomass/ha)], which is mainly for Asian broadleaved forests (FAO 2010). The area values are those given in the Global Forest Assessment Report.

Table 9: **Biomass variables from 1990 to 2010**

Variable	Unit	1990	2000	2005	2010
Growing stock	million m³	261	211	185	160
Weighted wood density		0.7	0.7	0.7	0.7
Stem biomass	million t	183	147	130	112
Forest area	'000 ha	2,527	2,116	1,902	1,687
Stem biomass/ha	t/ha	72	70	68	66
Biomass expansion factor		2.85	2.90	2.94	2.98

Source: FAO (2010)

Figure 13 shows the changes in different components. The total living biomass in Pakistan's forests decreased continuously from 704 million tonnes in 1990 to 453 million tonnes in 2010. The decreasing trend was observed in both above ground biomass and below ground biomass. The root-to-shoot ratio increased consistently but only very slightly from 0.347 in 1990 to 0.357 in 2010, which may indicate an increase in tree health.

Figure 13: **Biomass trends in Pakistan's forests from 1990 to 2010**
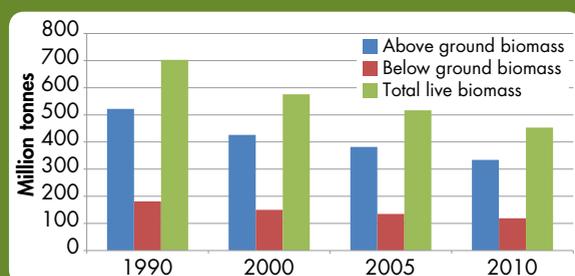
Pakistan's carbon stocks include carbon in above ground biomass, below ground biomass, dead wood, litter, and soil. No data on carbon were available to calculate carbon stocks directly, so a carbon conversion factor of 0.47 as recommended in the FRA guidelines was applied to the biomass; a default factor of 2.1 t/ha of carbon in forest litter was also assumed. Using these values, carbon in above ground carbon stock was calculated to have decreased from 245 to 157 million tonnes, and carbon in below ground carbon stock from 85 to 56 million tonnes, between 1990 and 2010. This situation is very different to that in

neighbouring countries. In Bangladesh, the forest above ground biomass decreased only slightly over the two decades from 1990 to 2010 from 148 to 143 million tonnes; in India, the forest above ground biomass increased from 2,616 to 3,291 million tonnes between 1990 and 2010; and in China, there was a significant increase in forest biomass from 1990 to 2010 and a further increase forecast in recent surveys. Thus, the biomass stock in neighbouring countries, especially developing countries, is increasing.

REDD+ and Pakistan

The World Bank launched the Forest Carbon Partnership Facility (FCPF) at the 13th Conference of Parties of the UNFCCC in Bali in 2007 with the aim of building capacity for REDD in developing countries and testing a programme of performance-based incentive payments in some pilot countries. The FCPF consists of a readiness mechanism and a carbon finance mechanism. Such programmes are active in Vietnam, Indonesia, Thailand, and Malaysia (IGES 2010).

The forest cover assessments described here show that there is a serious threat of accelerated deforestation and forest degradation in Pakistan. In order to address this issue, Pakistan has developed a voluntary REDD+ database (VRD) and joined the REDD+ Partnership that was formed in Oslo in May 2010, which serves as an interim platform for partner countries to scale up actions and finance REDD+ initiatives. Pakistan joined UN-REDD as a partner in 2011 and is set to operationalize and mainstream REDD+ in its forest management practices. In July 2013, Pakistan became a member of the Forest Carbon Partnership Facility (FCPF) and submitted a REDD+ Readiness Preparation Proposal (RPP) to the FCPF, which was approved and received USD 3.4 million funding over five years. Pakistan succeeded in securing a further USD 10 million through a GEF allocation under the Clean Development Mechanism and Climate Change, which also addresses REDD+ (Khan and Nasir 2011). The consultation activities have produced several important outcomes, including identification of a range of stakeholders relevant to REDD+ along with the outreach methods that enhance both collaboration and capacity building among national, provincial, and local level line agencies, and other organizations, and hence enhanced ownership of the REDD+ mechanism. Various capacity building needs were also identified during the consultation process. At present a project is being implemented on 'preparation of action plan and capacity building for a national forest monitoring system (NFMS) for REDD+'.

Monitoring, reporting, and verification

Monitoring, reporting, and verification (MRV) is a key element in reducing emissions under REDD or REDD+ in developing countries. It is a powerful method to assess and provide a true picture of the activities conducted, results, and improvement over time, and has become an integral part of any REDD+ strategy programme. In developing countries such as Pakistan, MRV can play a vital role in establishing guidelines, standards, and monitoring systems. However, certain issues need to be addressed before national emissions from deforestation

and forest degradation can be estimated accurately, including 1) the lack of clarity as how the verification of data accuracy is determined; 2) insufficient treatment of the issue of degradation; 3) only living biomass is covered; 4) available data is inconsistent; and 5) lack of harmonized definitions and classifications (MARD 2008; NDP 2009). The review of forest cover assessments presented here shows clearly the need for developing a consistent and reliable method for forest cover assessment from the national level to the local level in Pakistan.

In 2013, Pakistan launched the REDD+ Roadmap process and is now one of the REDD+ implementing countries under the UN-REDD programme (UN-REDD nd). Worldwide, a number of scientists are engaged in a wide variety of activities aimed at reducing emissions from deforestation, ultimately contributing to the REDD+ plans at every level. Gardner et al. (2012) studied national REDD+ programmes using a framework especially for developing countries. They reported that the assessment process occurs at an operational level in areas that have received REDD+ investments and can be implemented through different tiers of data requirement and complexity. The world-famous Amazon forests in Brazil cover a large range of green patches. A recent study conducted by Bottazzi et al. (2013) suggested two main approaches or methods to assess and address REDD+ issues in the Amazon: compensated reduction of emissions from clearing old-growth forest for agriculture, and direct payments for labour input into sustainable forest management combined with a commitment not to clear old-growth forest. In Pakistan, an interdisciplinary approach was used in different mega cities to assess the carbon sinks and stocks (Ali et al. 2012; Ali and Nitivattananon 2012). The land cover and land use changes were investigated and assessed using Landsat data, and changes in carbon sinks, particularly those in vegetation in urban areas, were investigated. The results showed that the sinks are decreasing. A similar assessment of mangrove was conducted by Abbas et al. (2013) in Pakistan. The learning from these activities will feed into the initiatives in Pakistan.

There are a number of initiatives in Pakistan that could contribute to addressing the challenges involved in developing an accurate assessment of national emissions from Pakistan's forests. For example, strengthening monitoring, assessment, and reporting on sustainable forest management includes tackling obstacles to information management. Outside the REDD+ process, Finland and the Japan International Co-operation Agency (JICA) have been working towards improving the development of a forest information system. In this system, data collection takes place at provincial level and is then centralized. FAO is supporting this programme financially, and so far it seems to be successful. More details of the REDD+ activities in Pakistan are provided in another paper in this volume (Hussain et al. 2015).

Potential sites for REDD+

In identifying potential sites for REDD+, it is important to consider the ecosystem services they provide. REDD+ can be particularly useful in conserving the services that are most important and also most under threat. Forest ecosystem services include ensuring that a watershed

provides clean water for human consumption, provision of timber and subsistence needs of local communities, provision of habitat for wild plants and animal species, and conservation of biodiversity. Although the proportion of forest cover in Pakistan is relatively low, there are some rich forest spots in different parts of the country which provide potential sites for REDD activities. The major sites include areas in Azad Jammu & Kashmir, Balochistan, Gilgit-Baltistan, Khyber Pakhtunkhwa, Punjab, and Sindh, all of which are special in terms of the presence of rare species and abundant forest ranges.

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Five Decades of Forest Monitoring in Nepal: From Photo Interpretation to Laser Scanning

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F orest inventories provide baseline information on a country's forest resources for planning and decision making. Inventories are generally based on a combination of assessment of the total extent of particular forest types, based on interpretation of wide area images, and detailed assessment of composition based on analysis of field sample plots. In Nepal, the inventory approach has changed in response to the changing needs and priorities of the country from simply estimating volume of commercial timber, to estimating carbon stocks, biomass, biodiversity, availability of non-timber forest products (NTFPs), and social variables. This paper provides a brief summary of the major forest inventory activities in Nepal since the 1960s, with more detailed information on the most recent inventory – the Forest Resource Assessment (2010–2014) – and its suitability for use in REDD+ monitoring, reporting, and verification procedures.

Keywords: forest inventory, Forest Resource Assessment, LRMP

Introduction

Forests play a central role in the current debate on climate change and climate change mitigation. They can act both as a source of greenhouse gases when they are destroyed, and as a sink when their area and density is increased. Forests also play an important role in the regulation of the hydrological cycle, in reducing soil erosion, in stabilizing sloping land, and in regional climate regulation, and they provide the basis for the livelihoods of people who live in and around forest areas. Notwithstanding their importance, forests are being degraded or destroyed in many parts of the world, often on a large scale. Increasingly, plans are being made to maintain and restore forests by compensating communities financially for their forest activities through such mechanisms as REDD+ (Reducing Emissions from Deforestation and Forest Degradation) and payment for ecosystem services (PES), both as a contribution to climate change mitigation and to ensure that forest ecosystem services are sustained.

Both compensation schemes and overall national and local planning require information about the extent of forest resources and change over time as a basis for decision making. This information is generally obtained through national and local forest inventories. However,

assessing the extent and state of forest in a country is a complex process, especially in mountainous countries like Nepal where forests are diverse, and much of the forested land lies in poorly accessible areas and the resources available for mapping are limited. Notwithstanding the difficulties, Nepal has carried out a series of forest inventories over the years.

Inventories are generally based on a combination of assessment of total extent of particular forest types, based on interpretation of wide area images (photos, satellite images, etc.), and detailed assessment of composition, based on analysis of the vegetation and soil in sample plots. Information from sample plots is used to obtain more detailed information on composition and specific variables and to relate these with parameters obtained from satellite imagery as a way both to guide and to verify the image analysis. In Nepal, the inventory approach has changed in response to the changing needs and priorities of the country from simply estimating the volume of commercial timber, to estimating carbon stocks, biomass, biodiversity, availability of non-timber forest products (NTFPs), and social variables. The first inventories used photographic images taken from aircraft and were limited to accessible areas. With the recent advances in remote sensing technology, and requirements for information on a much wider range of variables, Nepal is now moving towards the use of advanced approaches such as Lidar (light detection and ranging). The most recent approaches are suitable for preparing the detailed inventories required as a basis for financial compensation schemes. In this paper, we summarize the major forest inventory activities in Nepal since the 1960s as a basis for understanding the information that is available and the potential for future assessments. The most recent inventory, the Forest Resource Assessment, is described in some detail and the possibilities for use as baseline information in REDD+ activities is briefly discussed.

Historical Forest Inventory in Nepal

Several forest inventories were carried out in Nepal between the 1960s and 1990s with technical support from a number of countries including the United States of America, Canada, Finland, and Japan.

The first National Forest Inventory (1963–1967)

The first national-level forest inventory was conducted between 1963 and 1967 with technical collaboration from USAID. It covered the Terai, Inner Terai, Churia Hills, and southern faces of the Mahabharat Range, but excluded most of Chitwan Division, which was inventoried separately, and all the mountain areas, which were considered inaccessible. The forests were first classified as commercial or non-commercial. The survey focused on collecting data from the commercial forests, primarily in terms of estimating stocks of timber and domestic consumption of wood products. In terms of methodology, it was based on the visual interpretation of aerial photographs (1953–58 and 1963–64), mapping, and field inventory. This inventory provided the first comprehensive assessment of commercial forests in the Terai

and the adjoining hill regions. Following the national level inventory, district-level forest inventories were conducted in most Terai districts and some hill districts between 1968 and 1989 in order to assess growing stock and prepare district-level forest management plans.

The Land Resources Mapping Project (1978–1986)

Forest was included as one category in the country-wide Land Resources Mapping Project (HMGN 1986) carried out between 1978 and 1986 by the Nepal Government with support from the Canadian International Development Agency (CIDA). The study used aerial photographs from 1978 to 1979 at a scale of 1:50,000, together with the results of a nation-wide land survey, topographic maps at a scale of 1:50,000, and ground verification to map land cover and land use. Forest was defined as areas of trees with crown cover of at least 10%. Both high- and low-altitude forests were assessed and mapped in terms of dominant species and forest type (coniferous, hardwood, or mixed), size, and crown cover (10–40%, 40–70%, 70–100%). Scrubland was mapped separately. Land use maps were produced at a scale of 1:50,000 and the final reports were published in 1986 (HMGN 1986). The Master Plan for the Forestry Sector published in 1989 (HMGN 1989) used the land categories provided by the LRMP.

The second National Forest Inventory (1990–1997)

The second national forest inventory was conducted by the Forest Survey and Statistics Division (now Department of Forest Research and Survey, DFRS) under the Ministry of Forest and Soil Conservation (MFSC) with support from FINNIDA (Government of Finland) under the Forest Resource and Information System Project (FRISP) from 1990 to 1998 (DFRS 1999, Härkönen 2002). In the first phase, it updated data on forest coverage and other forest statistics, and identified change (especially deforestation) from 1987 to 1998 for all the accessible forests (all 20 Terai districts and selected hill districts) but excluding protected areas (PAs). Forest was defined as an area of at least one hectare where trees with well-defined stems are growing, with crown coverage more than 10%, not used primarily for other purposes, and at least 100 m wide (area could include treeless patches not wider than 25 m and not exceeding 1 ha). Inaccessible areas were defined as those located on a slope of more than 100% (45°) or surrounded by steep slopes, landslides, or other physical obstacles.

The first phase from 1990 focused on the Terai; the inventory was extended to the hill areas in 1994. The results provided realistic figures for forest and shrub areas as well as for growing stock categorized by tree species. More details of the inventory can be found in Härkönen (2002) and FAO (2007).

The Terai inventory (14 districts) was based on interpretation of Landsat TM satellite images (28.5 m spatial resolution) from 1990 and 1991. Normalized Difference Vegetation Index (NDVI) thresholding was applied to distinguish between forested and non-forested land. Forest and shrub could not be distinguished, but previous results indicated that the amount of shrub

in the Terai was insignificant. Field inventory was based on unsupervised classification of Landsat TM satellite imagery and field sample plots. The area of the sample plots varied according to tree diameter, ranging from about 80 m^2 for seedlings to 4,800 m^2 for big trees. The sampling intensity was about 0.015%.

Seven districts were assessed under a 'District Forest Inventory'. Forest areas were delineated in aerial photographs taken at a scale of 1:25,000 and 1:50,000 in 1989–1992 (Figure 14). Stratified random sampling and field study were used to estimate forest types, stand size, and stocking classes. Three districts were assessed under the Churia Hills Forest Inventory in a similar way to the Hill Area Inventory (below).

Figure 14: **Typical aerial photo used for sampling**

The Hill Area Inventory (51 districts) was based on black and white stereo-pair aerial photographs at a scale of 1:50,000 taken under a topographic mapping project for Nepal's development regions. Photos were taken in 1992 for the Eastern and Central Development Regions and in 1996 for the Western, Mid Western, and Far Western Development Regions. Topographic maps from the 1950s Indian Survey were used as topographic base maps. Photo-point sampling was used with a grid of 7,685 sampling points (4 × 4 km or 3.66 × 3.66 km). The grid was drawn on the topographic maps and transferred to the aerial photos to estimate forest area and to identify the position of sample plots in the field. Field inventory was carried out in sample plots selected using the same point grid overlaid on the maps. Altogether 560 clusters in 156 camp units were measured in the field. The size of sample plots varied according to tree diameter ranging from 50 m^2 to 3,600 m^2. The sampling intensity for the accessible forest in the hill area was 0.015%. The results for mean volume in the regions and hills overall are shown in Table 10 and the map of forest cover in Figure 15.
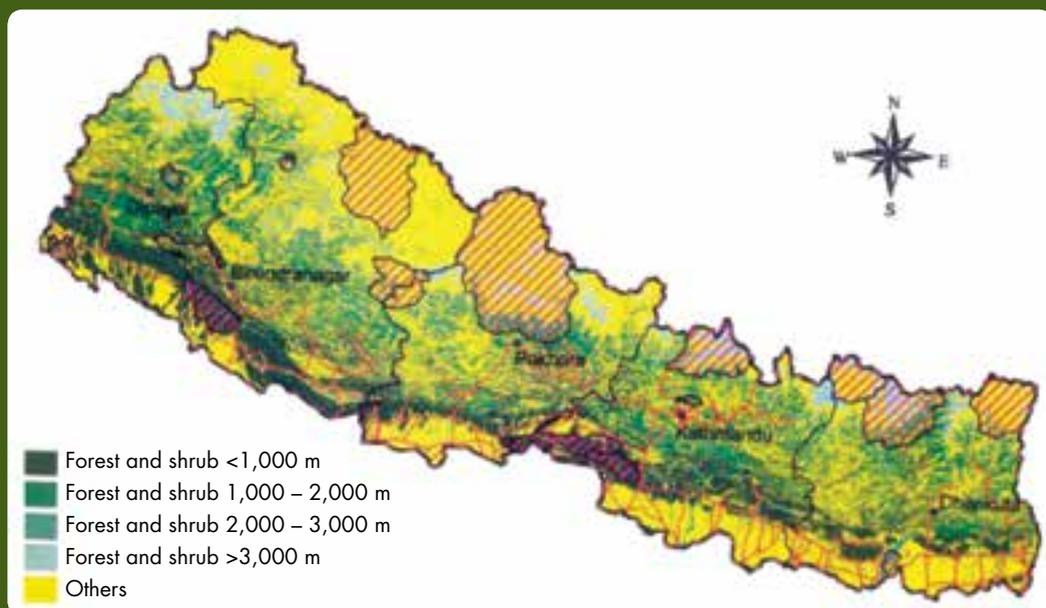
Wide area tropical forest resources survey (2000)

In 2000/2001, the DFRS carried out a national wide-area survey of tropical forest resources in

Table 10: **Mean volume in hill areas in 1994**

Development region	Mean volume 1994 (m³/ha)
Eastern	225.5
Central	185.0
Western	207.5
Mid-Western	171.1
Far-Western	218.1
Hill area total	200.5

Figure 15: **Forest cover map prepared in 1994**

Legend:
- Forest and shrub <1,000 m
- Forest and shrub 1,000 – 2,000 m
- Forest and shrub 2,000 – 3,000 m
- Forest and shrub >3,000 m
- Others

technical collaboration with the Japan Forest Technical Association (JAFTA) using satellite imagery (Landsat TM images from 1998/99 and Indian remote sensing from 1999/2000) (JAFTA 2000). The survey analysed land use, forest distribution, forest type, and conditions with the aim of providing the information required to prepare forest management plans. Six different types of forest were identified (sal, tropical mixed hardwood, upper mixed hardwood, chir pine, blue pine and fir/hemlock/spruce/cedar) with a total forest area of 5.51 million hectares, and shrub area of 1.28 million hectares.

Forest cover change (2005)

In 2005, the Department of Forests (DOF) conducted a study of forest-cover change in the 20 Terai districts using Landsat images from 1990/91 and 2000/01. Land was classified in six categories (forest, degraded forest, grassland, barren land, water bodies, and other land (DOF 2005; DFRS 2014b). Ground verification was carried out between September and November 2004. The total forest cover across the Terai districts (including the Churia Hills) was 37% (1.3 million hectares) with an annual rate of deforestation of 0.06% (excluding protected areas).

The Ongoing Forest Resource Assessment (2010–2014)

The most recent national inventory is being prepared under the Forest Resource Assessment (FRA) Nepal Project (2010–2014), a bilateral development cooperation project implemented by the governments of Nepal and Finland (www.franepal.org/). The project is specifically required to support the collection of the national-level baseline data required for the UN REDD+ programme (FRA 2013). The FRA has been designed to provide comprehensive, up-to-date national-level forest resource information for use in development of national forest policy and strategic forestry sector decision making. The assessment is intended to provide the distribution, extent, species composition, soils, and biodiversity characteristics of forests, together with data on forest change and estimates of timber volumes and carbon storage. To date, results have been published for two physiographic regions, the Terai (DFRS 2014b) and the Churia Hills (DFRS 2014a), and endorsed by the Government of Nepal. The national and middle mountain reports will be released soon.
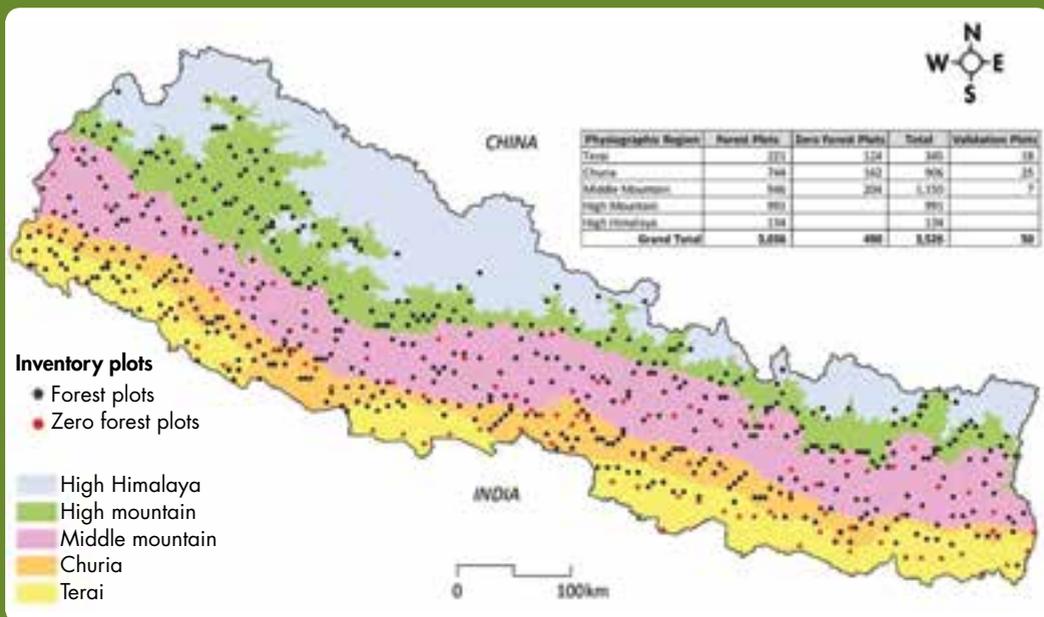
Sample design

The inventory design is based on 2-phase sampling with stratification and in some areas (Lidar Working Areas) 3-phase sampling with stratification. A 4 x 4 km grid was used for the first phase, giving a total of 9,180 clusters for the entire country; sufficient to provide accurate estimates for total forest area, other wooded land, other land with tree cover (trees outside of forests), other land without tree cover (agricultural land and built up areas), and others. Visual classification of high resolution and very high resolution satellite images (Figure 16) was carried out using six points per cluster, giving a total number of first phase sample points of around 55,000. Most of the points were easy to classify (clearly forest and clearly non-forest); some unclear points required more time and additional reference materials.

The second phase sample selected every fourth cluster with five or six wooded points; every eighth cluster with three or four wooded points; every twelfth cluster with two wooded points; every fifteenth cluster with one wooded point; and a very small fraction of clusters with zero wooded points. These relative proportions were defined after checking the first phase sample and distribution of clusters by number of wooded sample points. The idea was to select relative proportions such that clusters with several points in forest or other land with tree cover were more frequent in the second

Figure 16: **Rapid eye image used for mapping**

Figure 17: **Distribution of Forest Resource Assessment field inventory plots**

Inventory plots
- Forest plots
- Zero forest plots

High Himalaya
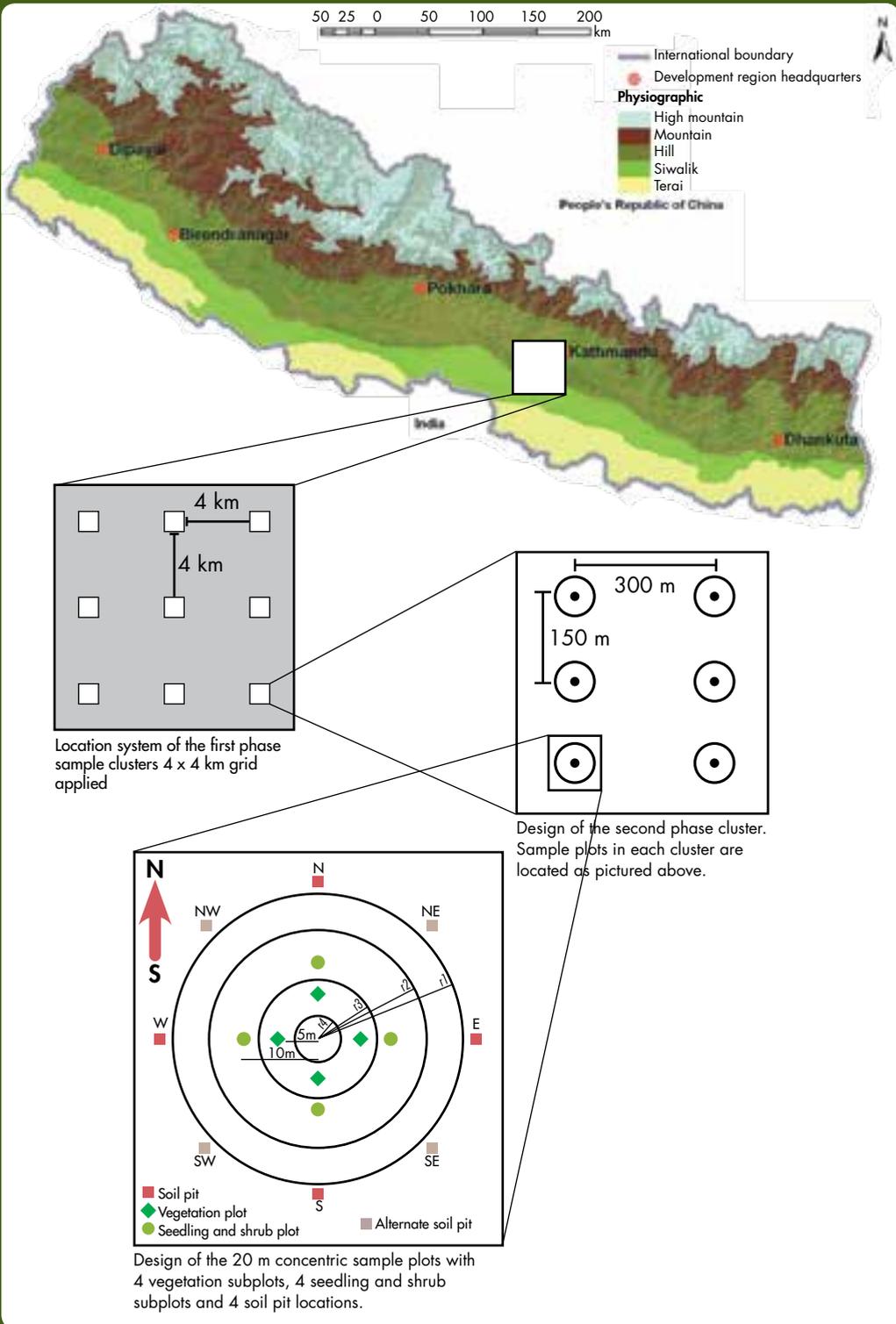High mountain
Middle mountain
Churia
Terai

phase sample than less wooded clusters. In the Terai region, most of the first phase clusters were either completely in forest or completely in agricultural land, thus an equal sampling intensity was selected for all clusters on forest plots. The distribution of field inventory plots is shown in Figure 17.

The design was used flexibly together with various remote sensing techniques and materials depending on the information needs in each physiographic region and applicability of remote sensing tools. In most cases, the FRA data provides good baseline data for further, more intensive forest inventories for management or other special purposes. Using this design, it was possible to calculate results for sub-units such as development regions (5 sub-units), physiographic zones (5 sub-units), and potential federal states (6 to 14 sub-units) that were still regarded as fairly accurate. The results for individual districts (75 sub-units) were not statistically reliable and subject to high errors due to the low number of clusters and measured field sample plots per district.

Field inventory

The field sample plots were established as permanent sample plots and positioned with a GPS-device. The location data were always entered when the measurement of a new sample plot was started. A concentric circular design was used (Figure 18). Sample plots were divided

Figure 18: **Sample plot design**

Location system of the first phase sample clusters 4 x 4 km grid applied

Design of the second phase cluster. Sample plots in each cluster are located as pictured above.

Design of the 20 m concentric sample plots with 4 vegetation subplots, 4 seedling and shrub subplots and 4 soil pit locations.

into two or more stands if there was a clearly visible different forest type or land use class within the plot. In these cases, stand delineation was required for estimating with respect to different forest stands (e.g., natural and planted forest) or land use classes within the plot. A forest stand, or forest compartment, was taken to be a forest that was homogenous with respect to administrative data, forest use restrictions, site factors, and characteristics of growing stock. Measurement started by defining and locating (delineating) the land use classes of the forest stands. Tree-level data collection was then divided into measurements of all trees and detailed measurements on a sample of trees. Sampling was done according to a clearly defined protocol. Data were collected on standard parameters including tree number, diameter at breast height (DBH), height, tree quality class, crown cover, and tree type. Standing dead trees were also measured. Details of fallen trees and woody debris were recorded in a 10 m radius plot. Shrubs and small trees (seedlings and saplings) were measured in four 2 m radius sub-plots located 10 m from the centre of the sample plot. Loose litter was measured by collecting from the soil surface of four 1 m² square sub plots located 5 m from the centre of the main plot. The characteristics of herbaceous plants, grasses, and pteridophytes were recorded in the same square vegetation plots. The percentage coverage of the vascular plants and ferns were determined in each vegetation plot. Soil samples were taken from square plots at four cardinal or sub-cardinal points. The surface was cleared and soil samples were taken at depths of 0–10, 10–20, and 20–30 cm.

Calculations

The tree volume was estimated using the models and equations given by Sharma and Pukkala (1990). Models are provided for 21 individual tree species and two additional tree species groups. The models were used to estimate total stem volumes over- and under-bark, and merchantable stem volumes up to tip diameters of 10 and 20 cm. Biomass estimates for stem, branches, and leaves were obtained using species-specific mean density estimates for stem wood and mean allocation coefficients for the ratios between 1) branch and stem biomass, and 2) foliage biomass and stem biomass (HMGN 1989). In order to adapt the existing volume and biomass predictors so that they could be applied to the FRA data for the Terai, decoding keys were established between the species listed in the FRA manual and the species modelled by Sharma and Pukkala (1990) and between the FRA species and species with biomass conversion factors (HMGN 1989), and were verified by local inventory experts. Stem volumes were converted into stem biomass by multiplying the predicted stem volume by the species-specific air-dried density estimate for stem wood (HMGN 1989) (Equation 1)

$$\hat{w}_{stem} = \hat{v}_{stem} \times \hat{\rho}_{stem} \tag{1}$$

where w_{stem} is stem biomass (kg), v_{stem} is stem volume (m³) and ρ_{stem} is the species-specific air-dried density estimate for stem wood (kg/m³).

The tree wise air-dried biomasses of branches and foliage can be determined using the equation for total stem biomass and mean ratio estimates in HMGN (1989) for the

relationship between branch and stem biomass, and foliage and stem biomass, respectively. A continuous estimator based on the species-specific ratio estimates by three tree size classes (small-, medium- and large-sized trees) was developed by Sharma and Pukkala (1990) (Equation 2):

$$
\begin{cases}
bmr_i = S, & \text{if } d_{1.3} < 10 \text{ cm} \\
bmr_i = [(d_{1.3} - 10) \times M + (40 - d_{1.3}) \times S]/30, & \text{if } 10 \leq d_{1.3} < 40 \text{ cm} \\
bmr_i = [(d_{1.3} - 40) \times L + (70 - d_{1.3}) \times M]/30, & \text{if } 40 \leq d_{1.3} < 70 \text{ cm} \\
bmr_i = L, & \text{if } d_{1.3} \geq 70 \text{ cm}
\end{cases}
\tag{2}
$$

where b_{mri} is the ratio estimator for the relationship between branch and stem biomasses ($i = w_{branch}/w_{stem}$) or foliage and stem biomasses ($i = w_{foliage}/w_{stem}$) of small-sized trees (S), medium-sized trees (M), and large-sized trees (L), respectively.

The biomass for the stump (including bark) and top coarse roots is predicted by multiplying the estimated volume by the air-dried density estimate for stem wood (HMGN 1989)

The mean volume (or biomass or any other metric variable measured in the plots) is only measured in the second phase sample plots. The mean volume (m³/ha) of a category k (e.g. forest type) in a sampling stratum h is estimated with the ratio of the means estimator (Kleinn 1994) (Equation 3).

$$
\overline{Y}_{hk} = \frac{\sum_i^{n_h} y_{ik}}{\sum_i^{n_h} a_{ik}} \times 10,000
\tag{3}
$$

where y_{ik} is the volume of trees in category k, a_{ik} is the area of plot i (m²), and a constant of 10,000 is needed to convert the figures to per hectare values.

Because concentric plots are used, each tree size class has a different plot size (a). One method to solve this is to use Equation 4 for each plot size and sum over size classes. Another computationally easier solution is to use a ratio estimator based on the number of plot mid points:

where Y_{ihk} is the per hectare volume (m³/ha) of a tree i in category k in stratum h (i.e., volume of each tree multiplied by its size dependent expansion factor), and n_{hk} the number of field sample plots (mid points) in category k in stratum h.

$$
\overline{Y}_{hk} = \frac{\sum_i^{n_{hk}} y_{ihk}}{n_{hk}}
\tag{4}
$$

Note: Y_{ik} is the volume of a single measured tree multiplied by its expansion factor. Even if the plot is not a full plot (part of it is not forest or outside the category k) the expansion factor is the expansion factor for a full plot, i.e. without any correction for plot size.

The mean volume of a category k over a sampling strata is estimated as the weighted mean of the sampling strata means (Equation 5):

$$\overline{Y}_k = \sum_n^L \overline{Y}_{hk} v_{hk}$$

(5)

where $v_{hk} = \dfrac{A_{hk}}{\big/ \sum_{h=1}^{L} A_{hk}}$ and A_{hk} is the area (estimate) of category k in stratum h.

Some recent results

The Terai and Churia Hills

The Department of Forest Research and Survey has published the most recent results of the ongoing national forest inventory for two regions: the Terai Forests (DFRS 2014b) and the Churia Forests (DFRS 2014a). Overall, forest cover was found to be decreasing and wood quality degrading. The main findings are shown in Table 11.

The percentage forest cover in the Terai region (20%) is less than a third of the percentage forest cover in the Churia region (72%). The value for other wooded land is also much lower (0.5% and 1.2%, respectively). Although the percentage of forest cover is higher in the Churia region, the productivity appears to be lower. Per hectare stem volume was higher in the Terai than in the Churia region (167 m³ compared to 154 m³). In both regions, sal forest has the highest biomass density.

The air-dried, above ground biomass of the Terai forests was 202.64 t/ha and the below ground biomass 6.09 t/ha. Per hectare air-dried and oven-dried biomass were estimated to be 208.73 t/ha and 189.75 t/ha, respectively. The total air-dried biomass and oven-dried biomass in the Terai forests were estimated to be 85.9 and 78.1 million tonnes, respectively. The largest stocks of soil organic carbon (SOC) were found in sal and tropical mixed hardwood forests; together, they contained 97% of the soil carbon stocks; the total carbon stock was 50.7 Tg (123 C t/ha). The Terai forests were highly disturbed by livestock grazing, tree cutting, sapling and pole cutting, tree lopping, and other human induced damage, and forest fires.

Table 11: **Values of main forest parameters in the Terai and Churia Hills**

Parameter	Terai region	Churia region
Forest area	20% (411,580 ha)	72.37% (1,373,743 ha)
Other wooded land (OWL)	0.47% (9,502 ha)	1.19% (22,672 ha)
Annual rate of change	-0.44%	-0.2%
Mean volume	167.42 m³/ha	153.99 m³/ha
Carbon density	123.14 tonnes/ha	116.96 tonnes/ha
Regeneration (seedling)	30,000/ha	19,805/ha
Biomass density	189.75 t/ha	175.28 tonnes/ha
Total carbon stock	50.68 Tg	160.65 Tg
Number of stem/ha>5cm	583 /ha	731 /h
Basal area	18.38 m²./ha	18.77 m²/ha

In the Churia Region, stem volumes were 154 m³/ha on forest land and 17.1 and 9.3 m³/ha, on other land, and other wooded land, respectively. Sal forest had the highest stem volume (192.3 m³/ha), pine the second highest (170.7 m³/ha) and khair/sissoo the least (12.8 m³/ha). The above ground air-dried biomass of live trees was 179 t/ha and below-ground biomass, 6.12 t/ha. The total (live trees, dead trees, dead wood) air-dried above ground biomass was 186.5 t/ha and the total below-ground biomass was 6.3 t/ha. The potential sustainable production forest was about 54% (744,000 ha). The total carbon stock in the Churia forest was estimated to be 160.7 Tg, with an average of 116.9 t/ha. Tree, litter/debris, and soil components contribute 84.7, 0.3, and 31.9 t/ha of carbon respectively.

Lidar scanning results

The Forest Resource Assessment Nepal, WWF, and the Arbonaut company collaborated to collect Lidar data for 5% of the Terai Arc Landscape (TAL) area in 2011. Twenty blocks of 20 x 5 km were scanned as a sample; 738 field plots with a radius of 12.6 m were inventoried in 2011, and 46 plots with a radius of 30 m were inventoried in 2013. The allometric equations developed by Sharma and Pukala (1990) were used to estimate the biomass. The correlation between Lidar data and field samples was estimated and wall-to-wall biomass estimates derived using the LAMP model and surrogate plots developed in the Landsat image in order to predict biomass and carbon.

The Government of Nepal has submitted a sub-national level Emission Reduction Project Idea Note to the World Bank based on the Lidar estimates in the TAL area; however, some issues related to ground verification and validation with inventory estimates and LAMP estimates remain to be resolved.

Conclusion

The current national forest inventory (2010–2014) in Nepal has created good baseline data at the national level that can be used both for future forest monitoring and for REDD+ monitoring, reporting, and verification (MRV) (activity data and emission factor data). However, some methodological issues remain in terms of how to integrate the national level inventory data with sub-national REDD projects that use advanced technology like Lidar for estimation. How to institutionalize procedures to ensure continuous future MRV based on principles of consistency, transparency, and reliability is also considered to be a key challenge for Nepal.

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2

Technology Trends:
Multi-Scale Remote
Sensing Using Active
Sensors

JAXA's Activities for REDD+

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*I*n this article, JAXA's MRV system is summarized. A spatial simulation model was developed based on time series synthetic aperture radar (SAR) data, an algorithm for forest/non-forest mapping, deforestation monitoring, and forest biomass mapping to fit the existing deforestation experience and project future forest patterns. Each step is introduced.

Keywords: forest/non-forest map, deforestation, biomass map, simulation

Introduction

Accurate mapping of forest cover is crucial for many applications, such as monitoring of forest processes, reducing uncertainties in global carbon modelling, and development of an MRV system (monitoring, reporting, and verification), and ultimately contributes to the effective implementation of reducing emissions from deforestation and forest degradation (REDD+) in developing countries. However, precise mapping of forest cover in wide areas of the tropics remains challenging (Hoekman et al. 2010). This is mainly due to the persistent cloud cover in tropical regions which has been a major barrier to creating spatiotemporally consistent forest land cover maps using the most popular optical sensing technique. In recent years, synthetic aperture radar (SAR) systems have altered this barrier significantly. SAR systems are active and stand alone in data acquisition. Space-borne SAR sensors available for civilian use operate in different bands of the microwave region (X, C, and L), which have the ability to penetrate atmospheric particles such as haze, smoke, and clouds without the limits of solar illumination (Achard et al. 2010; Shimada and Otaki 2010). The L-band is the lowest of the three frequencies but has a superior performance in signal penetration through the vegetation of the forest canopy, where radar backscattering, interferometric coherence, and phase information can be significantly linked with forest events.

JAXA's MRV system is summarized in Figure 19. The system is based on time series SAR data; the development is in progress. The current status for each category is presented in the following sections.

Forest/Non-Forest Mapping

At the global level, mosaics of ALOS PALSAR data were generated for 2007, 2008, 2009, and 2010 at 25 m spatial resolution. Maps of forest and non-forest were generated using

Figure 19: **JAXA's MRV system**

Note: C = carbon; CC = climate change; FNF = forest/non-forest; GT = Gigatonne; LULUCF = land use, land-use change and forestry; SAR = synthetic aperture radar
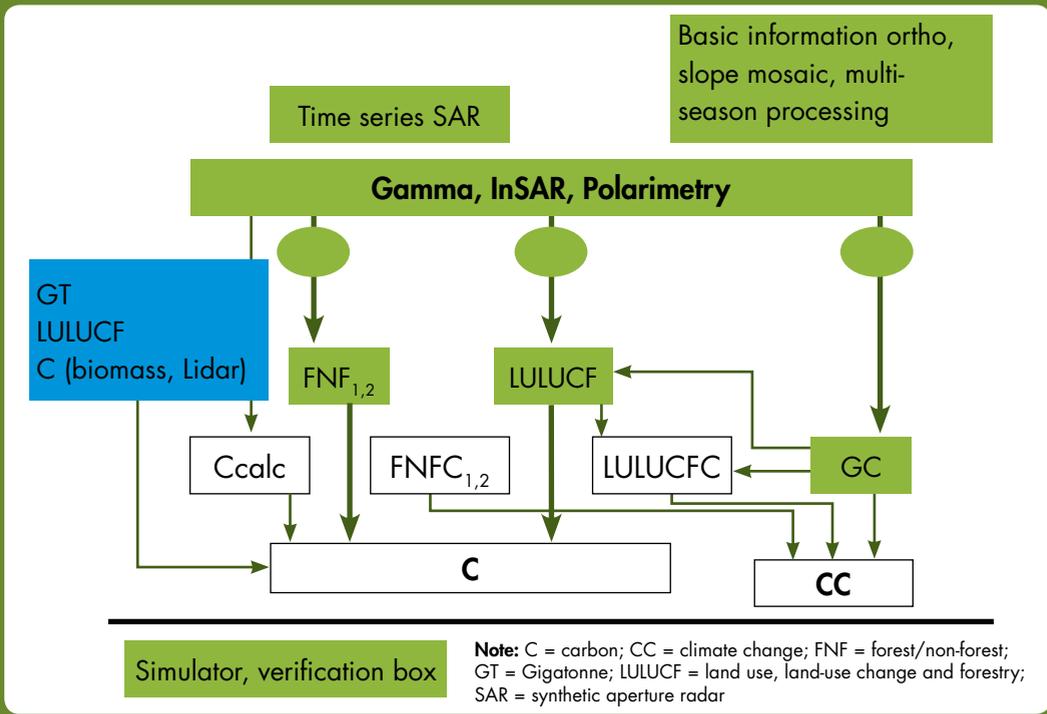
thresholds for HV polarization data that varied regionally. The accuracy of the mapping was assessed against Degree Confluence Project data, Forest Resource Assessment data, and Google Earth images; the overall agreement was 85%, 91%, and 95%, respectively (Shimada et al. 2014). Continuation of this work based on PALSAR-2 will be conducted after the launch of ALOS-2.

Annual Deforestation Monitoring in Indonesia Using ALOS PALSAR Mosaics

Time series γ^0 characteristics of natural forests and deforested areas were investigated using ALOS PALSAR gamma naught (γ^0) mosaics (Shimada and Otaki 2010), and the accuracy of automatic deforestation detection using a threshold was evaluated. The study area was Riau Province in Indonesia which has various forest types such as peat swamp forests, forests on mineral soil, mangroves, and plantations (oil palm, acacia, rubber, coconuts). Six ortho-rectified and slope-corrected γ^0_{HH} and γ^0_{HV} images from 2007–2010 were generated from fine beam dual (FBD) mode data using the SIGMA-SAR software (Shimada 1999); the pixel size was 25 m by 25 m. Truth data were extracted by human interpretation of time-series cloud free optical images (ALOS AVNIR-2 and Landsat 7 ETM+) and land cover maps.

A simple threshold for time series differences in γ^0_{HV} was effective in detecting the deforestation areas automatically (Figure 20). A fixed threshold for all data provided $72-96\%$ accuracy (average 87%). The difference to the accuracy derived by optimized thresholds for each time series data was only 2%. γ^0_{HH} did not provide such accuracy because γ^0_{HH} is unable to show systematic changes after deforestation occurrences.

One of the causes of detection error is temporal variation in γ^0. The temporal γ^0 variations in deforested areas were larger than those in natural forests. This different behaviour may decrease the accuracy. These γ^0 variations correlated well with accumulated precipitation. In the study, we averaged PALSAR data obtained at two different dates within one year to minimize the γ^0 variations. This can reduce the error and provide consistently high accuracy (average 91%, range 82–96%) but temporal resolution is reduced. This accuracy is compatible with the results of recent studies that used mid-resolution (10–60 m) optical sensors. The annual deforestation map obtained by applying the above method for PALSAR gamma naught mosaics over Riau Province is shown in Figure 21.

Figure 22 shows the area of natural forests in individual years; it shows that PALSAR data can provide yearly monitoring of forest areas, which is difficult to obtain from optical satellite images mainly due to persistent cloud cover. This type of information on forest cover change is one of the key parameters for estimating time series changes in forest carbon stocks. The PALSAR-based deforestation detection method has the potential to provide more detailed information, especially in tropical forests.

Biomass map

Biomass maps were produced from PALSAR data using two methods. Method 1 used land-cover classification results derived from PALSAR multi-temporal mosaic images (Shiraishi et al. 2014). The average biomass value for a class was taken as the representative value for that class, and assigned to the respective class. Method 2 used the correlation between radar backscattering (γ^0_{HV}) and forest above ground biomass (AG-biomass). The

Figure 20: **Areas in acacia plantations with decreased γ^0 (γ^0 change < -1 dB) (a); true colour images of ALOS AVNIR-2 RGB data (b,c,d)**

Figure 21: **Annual deforestation map of Riau Province obtained using ALOS PALSAR time series data**
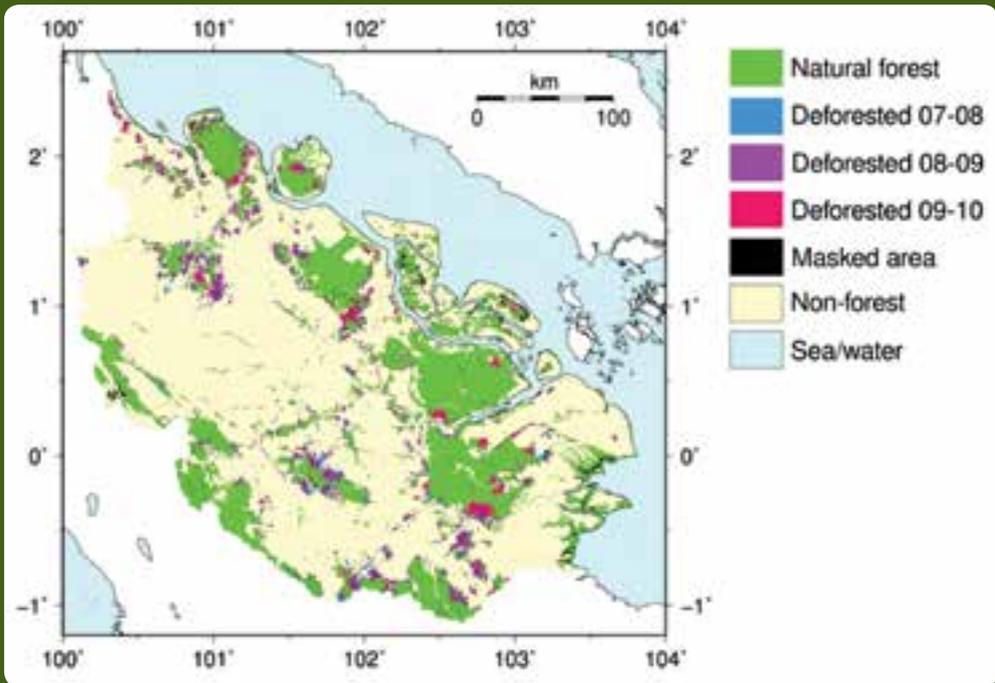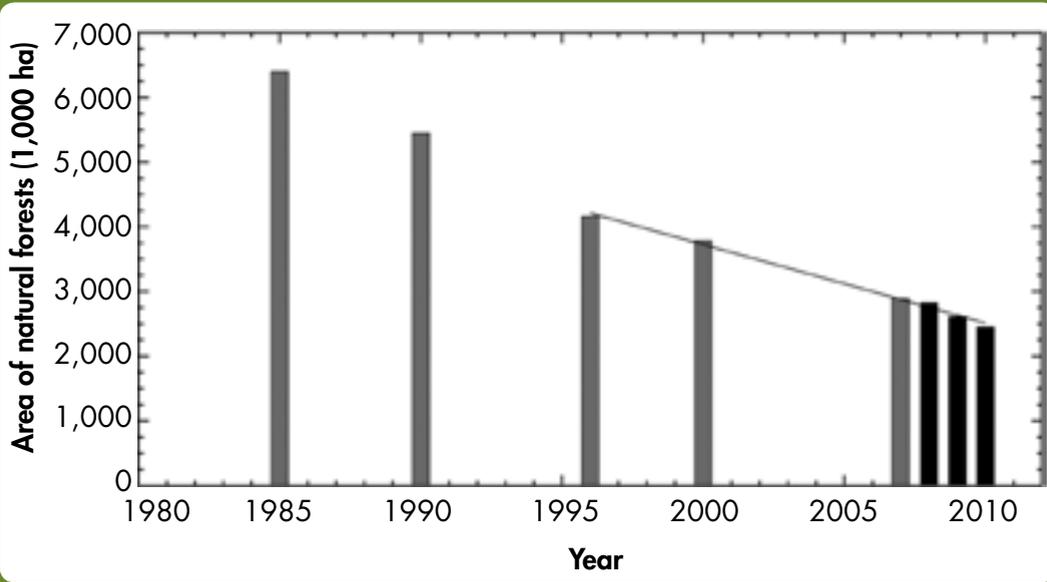

Figure 22: **Time series changes in the natural forest area in Riau province**

Data for the period 2008–2010 were calculated using the PALSAR mosaic deforestation map. Data for 1985, 1990, 2000, and 2007 were obtained from WWF Indonesia land cover data (Uryu et al. 2010). Data for 1996 were obtained from the report of Forest Watch Indonesia/Global Forest Watch (2002). The solid line shows the regression line for the data from 1996 to 2010, $y = -121.31 x + 246354$, $R^2=0.994$, $p < 0.001$.

γ^0_{HV}-(AG-biomass) relation derived using half of the biomass data (134 regions, each region 3.6 ha) and estimates from the Lidar data is presented in Figure 23. The solid line represents the fitting result with the water cloud model.

$$\gamma^0_{HV} = b_1 + b_2\,[1 - \exp(-b_3(AG\_Biomass))]$$

where b_1, b_2, and b_3 are free parameters

Root mean squared errors (RMSEs) for the biomass estimation were calculated using the water cloud model and the rest of the data.

Figure 24a shows the biomass map derived using Method 1. The total biomass in the study area was estimated to be 3.06 Gt. The average biomass value for natural forest estimated from 28 field biomass measurements was 256.1 t/ha with a standard deviation of 44% and range of 55–301 t/ha.

Table 12 summarizes the RMSEs for the AG-biomass estimation (Method 2). The simple average indicates that the value is estimated from the averaging of biomass derived from Lidar data and corresponds to Method 1. RMSEs were 62.8, when the γ^0_{HV}-(AG-biomass) relation was available. This value is smaller than the value of 99.1 estimated from a simple average. Figure 24b shows the AG-Biomass map produced with the γ^0_{HV}-(AG-biomass) relation.

Figure 23: **The γ^0HV-(AG-biomass) relation derived using half of the biomass data (134) and estimates from the Lidar data in Model 1.** The solid line represents the fitting result with the water cloud model.
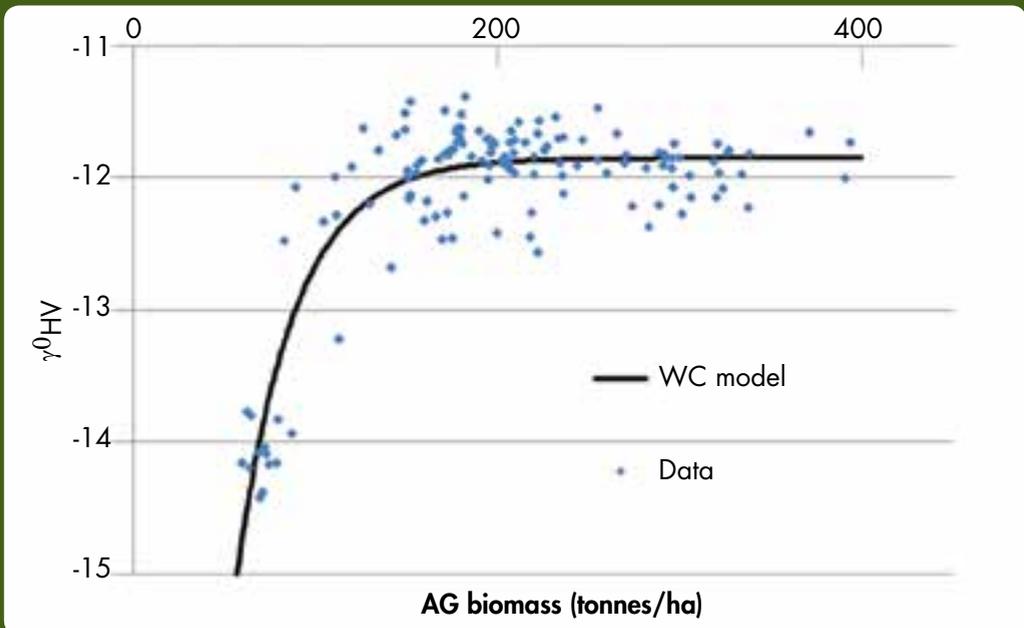
Table 12: **AG-biomass estimation error**

		AG-biomass (t/ha)	Std. Dev.[a]/RMSE[b] (t/ha)
Simple average		218.0	99.1[a]
AG-bio-mass – γ^0 (Model 1)	Total		62.8[b]
	< 100 t/ha		13.2[b]
	>100 t/ha	223.4	67.0[a]

The total biomass in the study area was estimated to be 3.23 Gt. The biomass value for natural forests was assigned to 256.1 t/ha for Method 1, as shown by the white in the biomass map (Figure 24a). The variation of biomass within a natural forest class as seen in the biomass map (Figure 24b) was as expected. The area surrounded by the blue rectangle in Figure 24b shows AG-biomass values of 30 to 100 t/ha. This area is called the peat dome, and is known as a very wet area containing less biomass, which is correctly reflected in the AG-biomass map.

Figure 24: **Biomass maps derived from a) the classification map and b) the relation between γ^0_{HV} and AG-biomass**

Linking PALSAR Observation to Forest Policies for Visualizing the Future Perspective of Tropical Forest

Tropical deforestation is considered to be a major source of greenhouse gas emissions and is expected to continue for the next several years. To reduce deforestation and forest degradation and mitigate forest-related GHG emissions, the United Nation's initiative for REDD+ is being developed to offer a financial value for the carbon stored in forests as an incentive for local communities. The requirement for the setup of a REDD+ programme is the monitoring, reporting, and verification (MRV) of baseline carbon stocks and their changes over time. Therefore, timely monitoring of tropical deforestation and investigating the future impact are essential. Integration of remote sensing and spatial modelling techniques is a promising tool for deriving the solutions. In this study, we investigated tropical forest loss and associated biophysical factors in Riau Province, Indonesia between 2007 and 2010 using time series PALSAR data, fieldwork, and other ancillary data. We developed a spatial simulation model to fit the existing deforestation experience and project future forest patterns.

Four what-if scenarios were formulated in the modelling and examined empirically (Thapa et al. 2013): business as usual (BAU); forest regeneration (FR); governance as conservation forest (G–CF); and governance through concession for plantation and selective logging (G–CPL). The model generated landscape spatial patterns indicated the potential locations

Figure 25: **Time series forest and deforestation patterns by scenario**
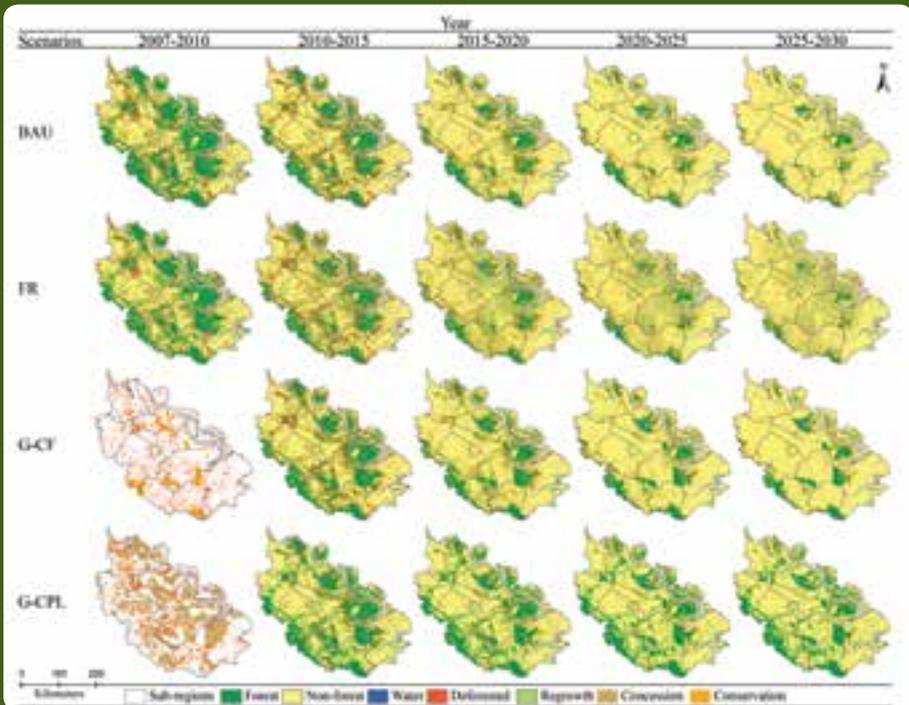
and extent of deforested areas by 2030 and provided crucial time-series information on the forest landscape under various scenarios for future landscape management projects (Figure 25). The results suggest that the current deforestation process is at a critical stage, where some local areas may face unprecedented stress on primary forest that will lead to loss of rivers and forest ecosystems as soon as the end of 2020. By quantifying the forest patterns and taking the BAU as a reference scenario from the REDD+ perspective, it can be calculated that the G-CF, FR, and G-CPL scenarios could save 1.67, 10.82, and 12.93%, respectively, of natural forest land from deforestation by the end of 2020. The landscape saving from deforestation under these scenarios is expected to be better in the subsequent decade (by 2030), i.e., 3.21, 15.17, and 18.88%, respectively. Each scenario derives a set of spatially explicit deforestation storylines with different possibilities incorporating simulations; which help people to grasp the possible risks and possibilities involved in particular courses of action by testing forest plans and strategies. The maps can be linked with the AG-biomass maps (Figure 24) to quantify the scenario wide future carbon emissions in the study area.

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Mapping Carbon Stock in the Community Forests of Nepal Using VHRS Images and Airborne Lidar Data

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*D*ifferent methods are used to measure above ground biomass (AGB) and thus the carbon stock of forests. Combining very high resolution (VHR) optical satellite data with airborne Lidar data has provided new opportunities to assess and map the carbon stock of forests accurately. The present study was conducted in a subtropical forest in Kayer Khola watershed, Chitwan District, Nepal. The retrieval of canopy height, crown projected area (CPA), and tree species classification was assessed, and their application in carbon stock estimation evaluated. WorldView-2 and Geo-Eye satellite data were co-registered and combined with airborne Lidar data to obtain a canopy height model. The main objective of the study was to map biomass and carbon stock in three community forests in Chitwan District, Nepal. Other specific objectives were to compare community and government forest management, assess the community forest certification process for sustainable forest management, assess forest trees species diversity, and develop a model base to estimate soil organic carbon.

Keywords: carbon stock, VHR satellite images, Lidar, community forest, Nepal

Introduction

The growing concentration of greenhouse gases (GHGs) in the atmosphere is thought to be the cause of increasing temperatures, and has raised concerns about global warming and climate change issues. Carbon dioxide (CO_2) is one of the main contributors to the greenhouse effect in the atmosphere. The global atmospheric concentration of CO_2 increased from 280 ppm in the pre-industrial era to 379 ppm in 2005, with an average increase of 1.9 ppm per year. Further increases in CO_2 and other gases are expected to lead to an increase in the global temperature by between 1.8 and 4°C by the end of the century (IPCC 2007). The rapid increase in CO_2 concentration is closely related to anthropogenic causes such as the heavy use of fossil fuels, deforestation, and land degradation. Deforestation and forest degradation are responsible for about 20% of GHG emissions, and are thus a major issue for climate change (World Bank 2010).

Carbon is sequestered and stored by terrestrial and marine ecosystems. About 2,500 gigatonnes of carbon (GtC) are stored in terrestrial ecosystems, compared to approximately 750 GtC in the atmosphere. Healthy forests sequester and store more carbon than any other terrestrial ecosystem and are considered to be an important natural brake on climate change (Gibbs et al. 2007). At present, forests cover around 31% of the total global land area and store a vast amount (289 Gt) of CO_2 in their biomass (FAO 2010). Forests sequester CO_2 from the atmosphere through the process of photosynthesis and act as a carbon sink. At the same time, some areas of forest are being destroyed, overharvested, burned, or converted to non-forest use, thus becoming a source of carbon emissions. Tropical forests represent a large pool of both carbon sinks and carbon sources, and the estimation of the carbon stock in tropical forests is crucial for understanding the global carbon cycle and reducing global warming.

The Kyoto Protocol to the United Nations Framework Convention on Climate Change (UNFCCC) contains quantified and legally binding commitments to limit or reduce GHG emissions at an average rate of 5% to the 1990 level over the five-year period 2008–2012 (UNFCCC 2011). All the contracting parties to the convention commit themselves to develop, periodically update, publish, and report to the Conference of Parties (COP) their national inventories of emissions by sources and removals by sinks of all GHGs using comparable methods. In addition, the Bali Action Plan of UNFCCC in 2007 (COP 13) opened windows of opportunity for developing countries to participate in forest carbon financing through the mechanism of 'reducing emissions from deforestation and forest degradation' (REDD) (UN-REDD 2009). REDD is an international effort to create a financial value for the carbon stored in forests. It offers incentives for countries to preserve their forestland in the interest of reducing carbon emissions and investing in low-carbon paths of sustainable development. The UNFCCC COP 15 meeting introduced the 'REDD+' mechanism, which is concerned with both reducing emissions and enhancing carbon stocks through actions that address deforestation, forest degradation, forest conservation, and sustainable forest management (UN-REDD 2009). To achieve the entire target, REDD+ will require the full engagement and respect for the rights of indigenous peoples and other forest-dependent communities.

Nepal is acknowledged and highly appreciated for its participatory forest management regimes. At present, approximately 39.6% of the geographical area of the country is covered by forests, 25% of which are managed by local and indigenous communities as community forest. The role of community forestry in REDD+ implementation is a central topic of discussion in Nepal's REDD process, and is likely to be an important component for an approach that is both environmentally effective and equitable. Nepal, as a UNFCCC signatory and a member of the UN-REDD Programme, has recently submitted a Readiness Preparation Proposal to participate in the Forest Carbon Partnership Facility. In order to further participate in the Carbon Finance Mechanism, Nepal has to show the current status of carbon stored in forests and emitted from deforestation and forest degradation. Therefore, it is crucial to estimate precisely the national forest carbon stocks in terms of biomass and sources of carbon

emissions to determine a national reference scenario and to develop a national REDD strategy. The main objective of the present study was to map biomass and carbon stock in three community forests in Chitwan District, Nepal. Other specific objectives were: to compare community and government forest management, assess the community forest certification process for sustainable forest management, assess forest tree species diversity, and develop a base model for estimating soil organic carbon.

Methodology

Study area

The study area was located in Kayer Khola watershed in Chitwan District (Figure 26), one of the 75 administrative districts of Nepal, which is located approximately 80 km southwest (260°) of the capital, Kathmandu. Chitwan District shares a common boundary with Dhading, Gorkha, and Tanahun districts to the north, and Rapti and Makawanapur districts to the east, and is bounded by the Narayani River to the west, and the international border with India to the south. Geographically, the district lies at latitude 27°30′51″–27°52′01″ N and longitude 83°55′27″–84°48′43″ E. The elevation ranges from 300 to 1,200 masl. The land is characterized by many steep gorges with slopes varying from 30% to more than 100%. The area is drained by the Kayer Khola River, which has many small tributaries.

Figure 26: **Location of the study area**
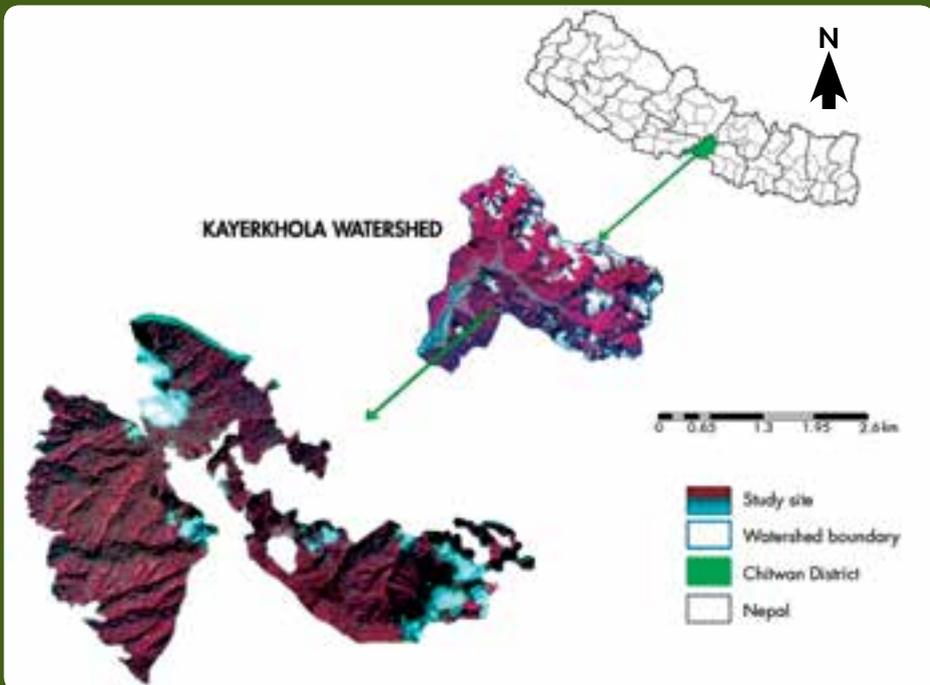
The district is famous for its rich natural resources and high quality timber. The study area has three main types of forest: 1) sal (*Shorea robusta*) forest; 2) hardwood forest; and 3) riverine khair-sissoo forest. Sal is the dominant tree species and comprises nearly 70% of forest composition. Other dominant tree species are *Terminilia bellirica, Schima wallichii, Semicarpus anacardium, Mallotus phillippensis, Cassia fistula, Cleistocalyx operculatus, Careya arborea, Holarrhena pubescens, Syzygium cumini, Aesandra butyracea*, and *Terminalia chebula*.

Research method

The overall research method is shown in Figure 27.

Results and Conclusion

Biomass, carbon, and diversity

Figure 28 shows the results of carbon mapping in the study area. WorldView-2 satellite imagery and airborne Lidar data are very promising remote-sensing sources for estimating and mapping the above ground carbon stock of tropical broadleaved forest in Nepal. The main technique used to estimate the carbon stock of the study area was a species specific regression model developed from the crown projected area (CPA) and height of the trees using object based image analysis (OBIA). The results showed that Lidar derived tree height was able to explain 76% of field measured tree height with an RMSE of 3.84 m. Pearson's correlation test indicated a statistically significant correlation between field height and Lidar height at $P<0.05$, whereas the F-test showed no difference between the means of the two heights. Transformed divergence among six major dominant tree species showed a best average separability of 1,970.99, which indicates a good separation among the species. NIR1, NIR2, and Red-Edge in the WorldView-2 image were found to be the best bands for spectral separability of different tree species in comparison to other visible bands in the image. The classification accuracy for classifying six dominant tree species was 58.1% and Kappa statistics 0.47; overall accuracy for classifying three dominant tree species was 72.7% with Kappa statistics 0.62. Two types of accuracy assessment were used for segmentation of the image: measure of closeness (D value) and 1:1 spatial correspondence. The overall D value for the study area was 0.33, with 0.29 over segmentation and 0.34 under segmentation, which means there was a 33% error (67% accuracy) in segmentation; 75% accuracy of segmentation was obtained from 1:1 spatial correspondence. Pearson's correlation analysis indicated a strong positive correlation ($r>0.70$) between height and carbon stock for five tree species. The correlation between CPA and carbon was 0.70, 0.79, and 0.84 for *Shorea robusta, Terminalia tomentosa*, and *Schima wallichii*, respectively, whereas a poorer relationship ($r< 0.70$) was found between CPA and height for all the species. On average the correlation coefficients of CPA and carbon, height and carbon, and CPA and height were 0.73, 0.76, and 0.63, respectively. Model validation results showed that species wise regression models were able to explain 94%, 78%, 76%, 84%, and 78% of the variation of the carbon estimation for *Shorea robusta, Lagerstroemia parviflora, Terminalia tomentosa, Schima wallichii*, and others, respectively.
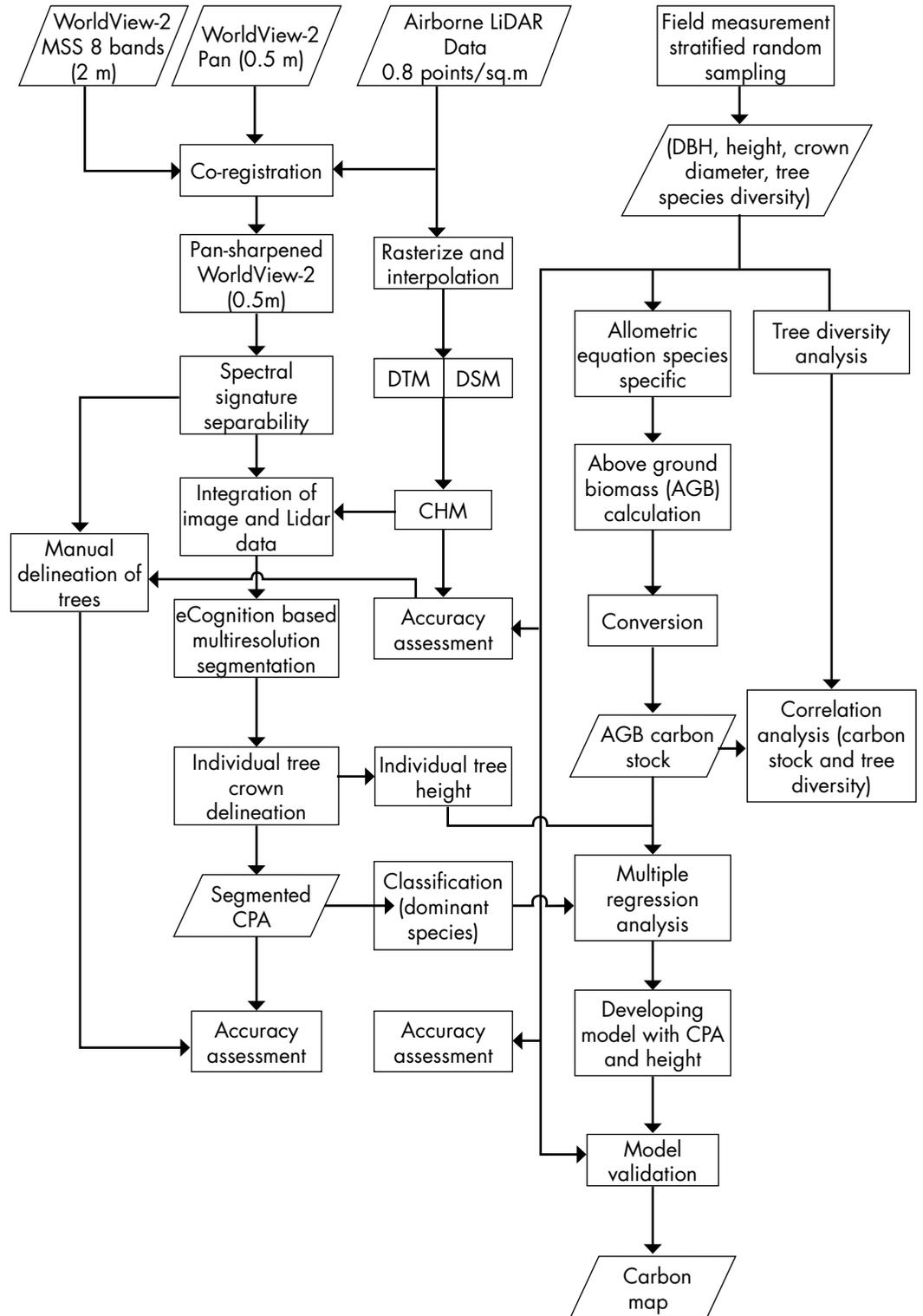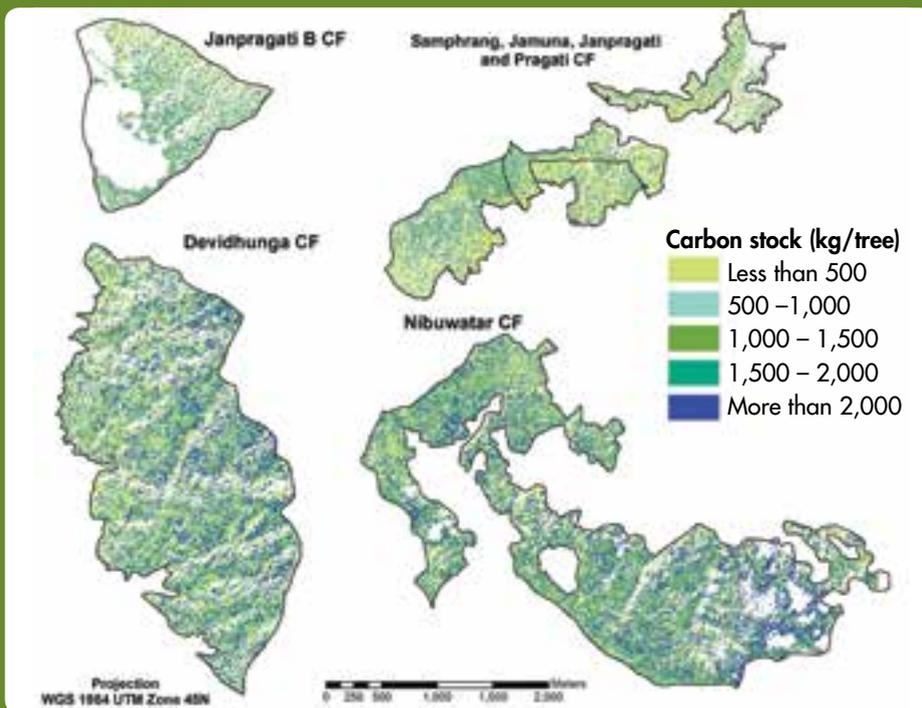
Figure 27: **Research method**

Figure 28: **Carbon stock map of community forests (CF) in the study area**

Sustainable forest management and timber certification

The integration of Lidar data and WorldView-2 imagery was evaluated for estimating and mapping indicators using OBIA to assess the condition and sustainability of three community forest areas in Chitwan (Devidhunga, Janprogati, Nebuwater). The selected five indicators were positively assessed with reasonable accuracy using Lidar data and WorldView-2 imagery. The segmentation accuracy was assessed using measure of closeness (D value) and 1:1 spatial correspondence. The 1:1 relationship showed an overall segmentation accuracy of 79%, while the D value (measure of closeness) gave a segmentation accuracy of 69%. The OBIA classification method was used for both forest type and species classification. The overall classification accuracy for forest cover was 94% for Devidhunga, 86% for Janprogati, and 82% for Nebuwater. The species classification resulted in an accuracy of 86% for classifying two species, 75% for classifying five species, and 67% for classifying six species. Two major forest cover types were found: forest and non-forest. At the more detailed species level, six dominant species were found in the study area: *Shorea robusta, Terminalia tomentosa, Schima wallichii, Lagerstroemia parviflora, Semicarpus anacardium*, and *Mallotus phillippensis*. A total of 243,079 Mg of above ground biomass (AGB), with an average of 367 Mg ha^{-1}, was found in the study area. The total timber volume was 222,143 m^3, and the mean timber volume 0.79 m^3/tree. The results of forest parameters, i.e., forest cover and area, species composition, AGB, and timber volume, were used to assess the status of each

community forest. For instance, the species diversity was comparatively low in Janprogati, and high in Devidhunga. More than 90% of Devidhunga and Janprogati was covered by forest, whereas 48 ha of non-forest area was found in Nebuwater. However, Nebuwater had a significantly higher AGB and timber volume than Devidhunga and Janprogati.

Forest management

The synergistic use of very high resolution (VHR) GeoEye satellite images and airborne Lidar data was evaluated for AGB/carbon stock estimation and comparison of two forest management regimes. AGB/carbon was estimated using interactive regression models, specifically one for *Shorea robusta* and one for 'other species' for each of the forests. The accuracy of estimation for community forest was $R^2 = 0.81$ with RMSE = 10% for *Shorea robusta*, and $R^2 = 0.62$ with RMSE = 13% for other species. The accuracy for the government-managed forest was $R^2 = 0.69$ with RMSE = 25% for *Shorea robusta*, and $R^2 = 0.73$ with RMSE = 13% for other species. This means that the prediction accuracy for *Shorea robusta* in community forest (90%) was much better than that for the same species in government-managed forest (75%). On the other hand, the prediction accuracy for other species in both forests was the same (87%). The average carbon stock for community forest was approximately 244 t C/ha, while that for government-managed forest was approximately 140 t C/ha. The results of the average carbon stock and t-test revealed that there is a significant difference in carbon stocks for the two forest management types. AGB/carbon stock is a function of stand density, basal area, species composition, and canopy density, and other factors that have not been dealt with in this study. These are influenced by the forest management practices. The results of this study showed significant differences in these variables in the two forests, which in turn led to a difference in their estimated average carbon stocks. The results show that there is a strong relationship between forest management practice and AGB/carbon stock. Although only limited attention was paid to assessing deforestation in this study, the primary data, basic observations during fieldwork, and site statistics analysis (stand density, canopy density models), suggest that there is some level of deforestation in the government-managed forest. The tree density for community forest was 397 trees/ha, while that for government-managed forest was 120 trees/ha. Thus there appears to be a significant difference in stand density in the two forest types.

Soil organic carbon

The study aimed to assess the effect of elevation, above ground biomass, and tree species diversity on soil organic carbon (SOC) and to develop a model to estimate SOC stock using airborne Lidar and high resolution WorldView-2 measured variables rather than direct measurement of soil samples. The results were as follows. The correlation matrix and stepwise regression showed that elevation and SOC are positively correlated. The strong correlation (r = 0.74) was thought to reflect the strong correlation between above ground biomass and elevation. Figure 29 shows the predicted SOC map. All variables are interconnected within the system and it is difficult to measure the influence of individual variables on each other.

Thus in a backward regression model, elevation individually didn't predict SOC. When elevation is related to species diversity, AGB, and soil bulk density, it can predict SOC. But in this model, species diversity and bulk density were not significant (p values of 0.11 and 0.15, respectively).

This study showed a strong positive correlation between SOC and AGB (at 95% confidence interval, p value < 0.001). Based on a backward stepwise regression model, AGB can predict SOC when it is correlated with elevation, species diversity, and bulk density. In similar way, based on a forward stepwise model, AGB can predict SOC when AGB is correlated with litter quality (p = 0.07). Based on the results of the stepwise regression, it was found that litter quality is very marginally correlated (p = 0.07) with SOC and can predict SOC in relation to AGB. In this study, litter quality was the representative index for species type. From this, it can be concluded that there is a marginal correlation between SOC and species type. However, there was a poor correlation between species diversity and SOC. When species diversity is used to predict SOC in relation to AGB, bulk density, and elevation, the significance level of species diversity was very low (p = 0.11).

From the findings of the study, it can be summarized that the following model is the best fit model based on the AIC and p value of the stepwise regression procedure. SOC can be measured using two remotely sensed variables, AGB and litter quality. The coefficient of

Figure 29: **Map of soil organic carbon**
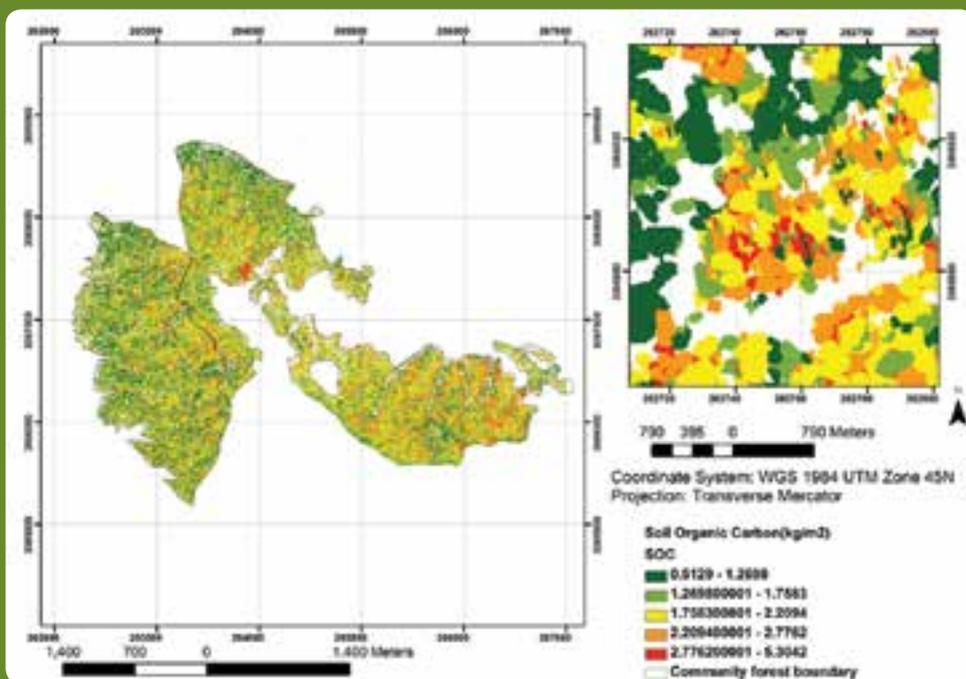
determination (R^2) indicates that 66% SOC can be measured using this model. The model predicted an average value of 1.77 SOC (kg/m^2) within the 0 to 10 cm soil layer in Chitwan District, Nepal.

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Exploring the Use of Spaceborne SAR for Above Ground Biomass Measurements in the Hindu Kush Himalayan Region and Pakistan

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*F*orests cover around 31% of the total global land area and the carbon stored in their above ground biomass (AGB) is directly impacted by deforestation and degradation. Regional scale AGB estimation using coarse and medium resolution optical datasets becomes problematic in sites with a complex forest structure, and where estimation using high-resolution data is hampered by the small area of coverage, frequent lack of availability of data, and topographical effects. Both low- and high-resolution datasets are also restricted by cloud cover. Airborne Lidar systems have been used for forest AGB estimation, but only with coarse spatial sampling; furthermore, a huge amount of logistic support is required for flight planning and execution. Spaceborne synthetic aperture radar (SAR) offers high resolution, cloud-penetrating, earth observation capability and is independent of nearly all weather conditions. At low-frequencies (P- and L-bands), spaceborne SAR penetrates the tree canopy, and the backscatter varies with biomass up to a certain AGB density threshold. Many recent studies have shown the use of L-band SAR for forest biomass estimation. An overview is given here, and specific issues on the usage of SAR for forest biomass estimation in the Hindu Kush Himalayan (HKH) region are discussed (HKH region overall and Pakistan specifically). Understanding the possibilities and limitations of SAR for forest biomass estimation in this region is essential in order to plot the future course of action for research in this direction.

Keywords: SAR, biomass

Introduction

Forests cover around 31% of the total global land area and store a vast amount (289 Gt) of CO_2 in their biomass alone (FAO 2010). The carbon stored in the above ground living biomass of trees is typically the largest pool and is directly impacted by deforestation and degradation (Yang et al. 2013). Different approaches based on field measurements, remote sensing, and geographic information system (GIS) modelling are widely used for biomass estimation (Goetz et al. 2009; Lu 2006). According to the Intergovernmental Panel on

Climate Change (IPCC) Good Practice Guidance (IPCC 2003), remote sensing methods are especially suitable for independent verification of the national land use, land use change, and forestry (LULUCF) carbon pool estimates. Accurate biomass estimation and mapping is vital for better understanding of the carbon cycles in terrestrial ecosystems (Houghton 2005). Active and passive optical remote sensing datasets and methodologies are commonly used for quantification of biomass and carbon stock estimation (Goetz et al. 2009). Despite several advantages, however, these systems have limitations in terms of accurate and reliable linkages between ground realities and remotely sensed datasets in terms of the monitoring, reporting, and verification (MRV) system for REDD+ (Reducing Emissions from Deforestation and Forest Degradation).

Coarse and medium optical spatial resolution data, such as Moderate-Resolution Imaging Spectroradiometer (MODIS) and Landsat Thematic Mapper (TM) provide a potential for above ground biomass (AGB) estimation at a regional level, but mixed pixels and data saturation lead to problems in AGB estimation at sites with complex biophysical environments (Gibbs et al. 2007; Lu 2005). Very high spatial resolution data provide more accurate results than coarse and medium resolution satellite data, but commercial data availability and the small coverage area are obstacles to use. In high resolution datasets, the complex forest stand structure means that shadows caused by the tree canopy or topography affect the accuracy of biomass estimation (Steininger 2000). Achieving high pixel-to-pixel positional accuracy in multi-temporal very high resolution datasets is also challenging (Potere 2008). Another drawback of high resolution satellite data until recently was the limited spectral variation. This has now been overcome to a large extent by the launch of satellites like WorldView-2. However, there is still a long way to go to resolve the issues of topographical and positional adjustment. A major restraint to the use of passive sensors in the visible and infrared range is that they cannot penetrate through clouds. The Hindu Kush Himalayan (HKH) region is often covered by clouds, which present a big challenge in acquiring suitable multi-temporal datasets to understand the seasonal variations in vegetation in terms of biomass and carbon.

Several airborne and space-borne small- and large-footprint Lidar systems have been used to make measurements of vegetation. The Lidar waveform signature from large-footprint instruments such as Scanning Lidar Imager of Canopies by Echo Recovery (SLICER) and Laser Vegetation Imaging Sensor (LVIS) has been successfully used to estimate tree height and forest AGB (Drake et al. 2003; Sun et al. 2011). Simard et al. (2011) have derived a global inventory of forest canopy height at 1 km resolution using the Geoscience Laser Altimeter System (GLAS) Lidar onboard Ice, Cloud, and land Elevation Satellite (ICESat). However, one major limitation of spaceborne Lidar systems is the lack of imaging capabilities and the fact that they provide sparse sampling information on the forest structure (Sun et al. 2011). Hyyppä et al. (2008) reviewed methods for small-footprint airborne laser scanning for extracting forest inventory data and concluded that the extraction of forest parameters through airborne laser scanning in high-relief terrain is challenging. ALS can only cover very small areas and also requires considerable financial and logistical resources to fly over certain areas with special approval needed for flight campaigns.
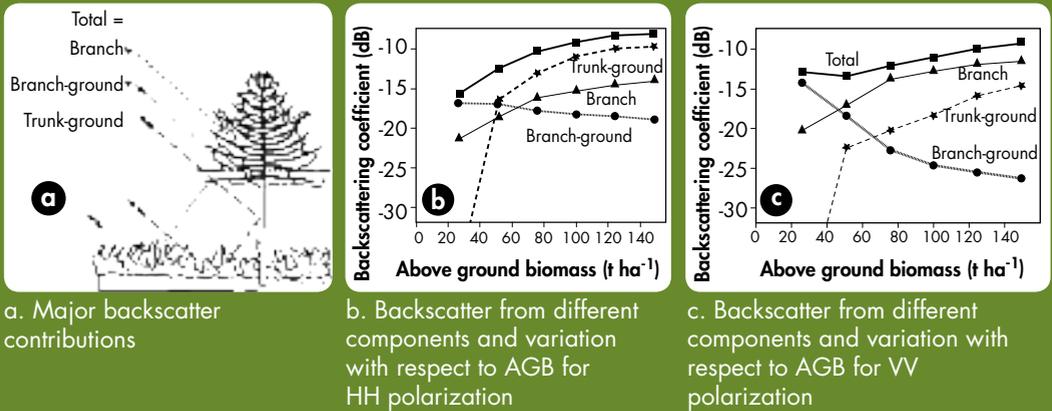
The idea of using airborne or spaceborne radar followed by higher-resolution synthetic aperture radar (SAR) to extract AGB measurements from forests has been around for some time. The primary advantages of SAR in this context are cloud penetration and through-canopy backscatter at certain frequencies. It is now well established that longer wavelengths (L- and P-band) penetrate through the canopy and go through multiple backscatter from canopy, trunk, stem, branches, leaves, and soil. Often, there may be multiple-bounce backscatter too, such as stem-ground. So, in theory, under certain feasible imaging conditions, low-frequency SAR backscatter contains contributions from all components of AGB. However, in practice, it is not a trivial task to extract this information from SAR datasets. Previously, backscatter models have been used; Michigan and Santa Monica microwave canopy backscatter models have been popular. Of late, statistical methods to calibrate models and measurements against reference biomass measurements (e.g., from ground surveys or Lidar campaigns) have been used to derive biomass from SAR measurements. Koch (2010) in a comprehensive review of laser scanning, SAR, and hyperspectral remote sensing data for forest biomass assessment also discussed advances in the use of SAR, especially combined with polarimetry and interferometry for biomass estimation. In a good summary of the topic, Woodhouse et al. (2012) note that while the relationship of radar backscatter with AGB is still not known under all forest conditions, satellite-based radar is a most useful tool for "mapping forest extent, estimating forest structural variability, and detecting deforestation and degradation".

Current State of the Art

Efforts to model and characterize radar backscatter from forest canopies were started in the late 1970s, and notable progress was made through the radiative-transfer based 'Michigan microwave canopy scatter model' (Ulaby et al. 1990). For woodland vegetation, the 'Santa Barbara microwave backscatter model' was developed (Wang et al. 1993). The use of a macroecological model was proposed by Woodhouse (2006). It is now well-established that at low frequencies (P- and L-bands) the radar backscatter is composed of backscatter contributions from canopy, trunk-ground interactions, canopy-ground interactions, and in some cases, also direct surface backscatter (Beaudoin et al. 1994; Wang et al. 1998). Figure 30 (adapted from Beaudoin et al. 1994) is a good graphical representation of the backscatter components for low-frequency (P-band in this case) backscatter from forests at 45° incidence angle. Figure 30a is a graphical representation of the major backscatter contributions, while Figures 30b and 30c show the backscatter variation with respect to AGB for horizontal-horizontal (HH) and vertical-vertical (VV) polarization, respectively.

Attempts to derive accurate AGB measurements from SAR backscatter measurements have generated mixed results, and a clear need has emerged for calibration using either ground measurements, Lidar campaigns, or field surveys. Hyde et al. (2007) found that using X-band and P-band SAR with Lidar data did not noticeably increase the AGB measurement accuracy, and they concluded that Lidar is a much better instrument for AGB measurement than SAR. In

Figure 30: **Modelled results of major contributions to radar backscatter from forest canopy at P-band frequency and 45° incidence angle**

a. Major backscatter contributions

b. Backscatter from different components and variation with respect to AGB for HH polarization

c. Backscatter from different components and variation with respect to AGB for VV polarization

Adapted from Beaudoin et al. 1994

contrast, preliminary results from Sun et al. (2011) show that using Lidar and SAR datasets in synergy can be very useful for AGB estimation. Sun et al. (2000) explored the use of Spaceborne Imaging Radar-C (SIR-C L-band horizontal-vertical (HV) polarization data to map forest biomass in mountainous areas, and their basic results were encouraging. A recent paper (Rahman and Tetuko Sri Sumantyo 2013) gives a very good summary of previous work done on estimation of forest biophysical parameters using SAR backscatter data over different regions and different forest types (see Table 13 in that reference). Woodhouse et al. (2012) give a good short note that describes the current problems with estimation of biomass from SAR and its interpretation.

Since there is no legacy of spaceborne SAR at P-band frequency, which may perhaps be most useful for canopy-penetration, further discussion will now focus on the L-band for which we have legacy spaceborne sensors (JERS-1, ALOS-1) and the recently-launched ALOS-2. As a side-note, the first P-band SAR satellite, the European Space Agency (ESA) BIOMASS mission, is being planned for launch in 2020. L-band backscatter is directly proportional to effective vegetation water content and soil moisture, and is good for estimation of woody AGB when surface moisture and rainfall are minimal (Lucas et al. 2010). Other studies show that radar polarization also plays an important role. Horizontal-horizontal (HH) polarization has more penetration through forests than vertical-vertical (VV) polarization (Lang and Kasischke 2008). Many studies show that L-band cross-pol horizontal-vertical (HV) backscatter has the best correlation and is the most sensitive to AGB (Kasischke et al. 2011; Robinson et al. 2013, and references therein in Sec. 4.2). Others, such as Dobson et al. (1995), show that SAR backscatter is also dependent on forest structure. At smaller incidence angles, radar penetrates further into the forest and provides better sensitivity to forest structure or volume. However, small incidence angles also cause complexity by causing direct backscatter from soil to make a contribution (Robinson et al. 2013); an interesting result is also shown in this study,

that AGB estimation from L-band SAR is more accurate at larger spatial scales up to 1 ha than at small spatial scales. Overall, it is now well-established by many published studies that L-band backscatter is directly proportional to AGB until it reaches a saturation point with respect to AGB density, and that this saturation point depends on forest and ground characteristics, radar wavelength, and polarization (Cartus et al. 2012a,b; Dobson et al. 1995; Lucas et al. 2010; Mitchard et al. 2009). A general range for this L-band saturation point is 100-150 Mg/ha (see Lucas et al. 2010, and Figure 7 and Table IV therein).

Recent efforts to derive AGB from L-band SAR measurements have been focused on calibration with biomass measurements from other methods. Cartus et al. (2012b), for example, used the Water-Cloud Model (WCM) to derive regional scale biomass from HH and HV multi-polarization L-band backscatter, ignoring higher-order interactions like stem-ground interactions. The model was calibrated via regression with reference optical-based biomass measurements. Their results agreed with earlier findings that HV backscatter gives higher biomass retrieval accuracy than HH backscatter. In another study (Cartus et al. 2012a), the Random Forest Regression Tree Model was used as a fusion and modelling tool for biomass estimation between airborne Lidar, Landsat ETM+, and ALOS PALSAR. The results from this study showed that the combined use of all these datasets yielded higher biomass retrieval accuracy than each dataset alone. He et al. (2012) derived AGB measurements from ALOS PALSAR L-band SAR data by regression with Lidar-derived biomass; their results, however, did not indicate SAR to be very useful for forest biomass measurements. Englhart et al. (2011) also used Lidar biomass measurements as a calibration source and derived biomass from both X-band (TerraSAR-X) and L-band (ALOS PALSAR) data. Their observation that L-band backscatter is more sensitive to AGB than X-band backscatter agrees with earlier studies; however, they also propose that use of X-band and L-band backscatter together might lead to even better AGB estimates from SAR.

The Way Forward for the Hindu Kush Himalayan Region and Pakistan

The IPCC recognizes the Hindu Kush Himalayan (HKH) region as a 'data-deficit area' (IPCC 2007), and there are no readily available regional scale biomass inventories. A global-scale forest growing stock biomass assessment was made by Kindermann et al. (2008) based on the United Nations Food and Agriculture Organization (FAO) 2005 statistics (FAO 2005). Datasets for this global inventory are publicly accessible through the International Institute for Applied Systems Analysis (IIASA) web portal. AGB measurements for the HKH region were extracted from the Kindermann datasets (Kindermann et al. 2008) and mapped; the results are shown in Figure 31. This derived global-scale dataset has certain limitations, and the reliability of global-scale figures is always a challenge at the regional and national level in terms of the statistics and accuracy. Nevertheless, the maps can be seen as general indicators of biomass distribution in the HKH region.

Figure 31: **Global scale above ground biomass inventory at a resolution of 0.5° x 0.5° (a) for the HKH region and (b) for Pakistan**
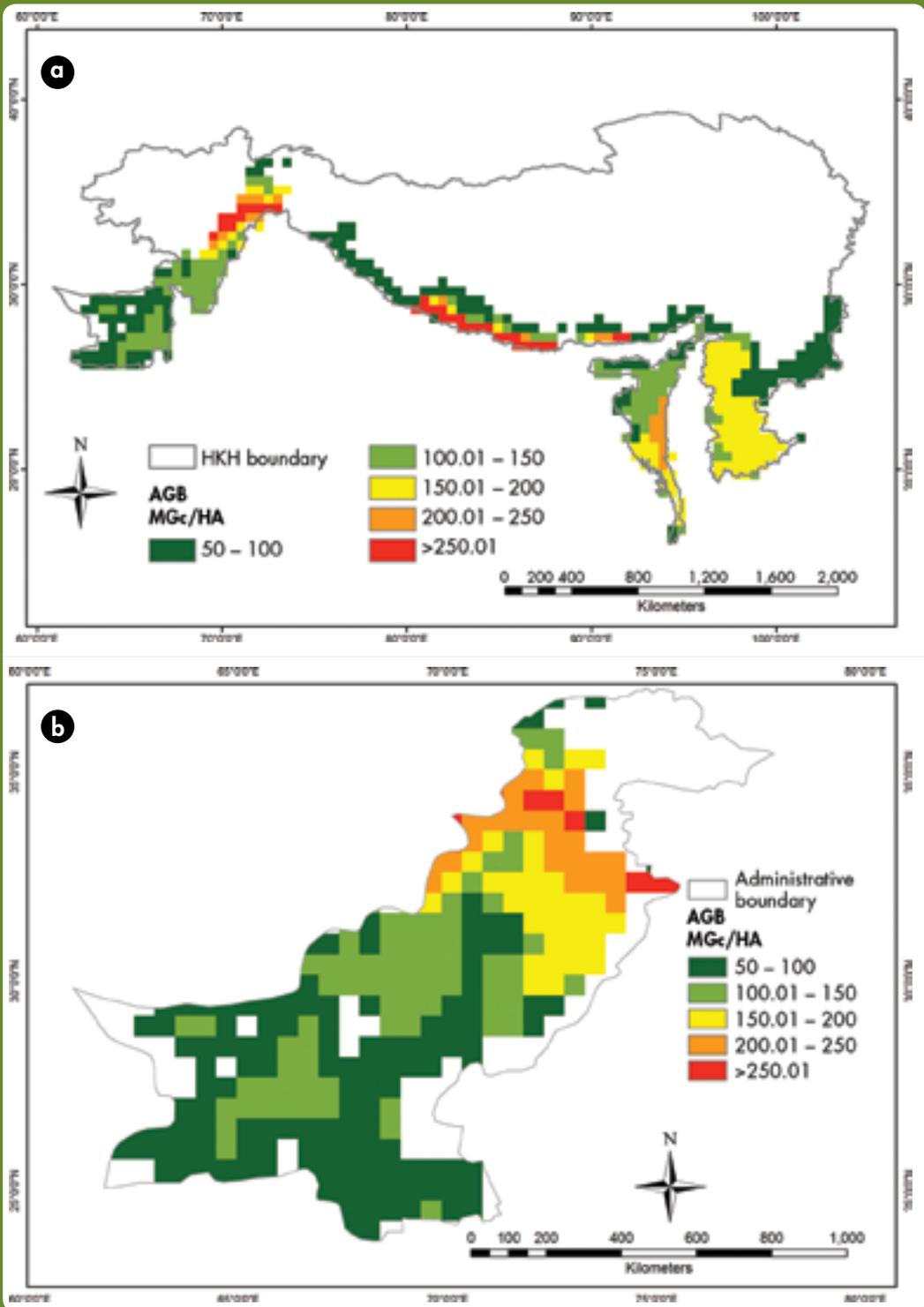
Based on the global biomass inventory developed by Kindermann et al. (2008) using FAO statistics

Figure 31a shows the global scale AGB density map for the whole HKH region. There is a large range of AGB density values, especially in the South Asian region. Keeping in mind the general saturation threshold of ≈150 MgC/ha for L-band backscatter, it may not be feasible to attempt biomass retrievals from SAR over huge areas where the biomass density is higher than this threshold. The saturation threshold also depends on many other variables, such as moisture content and forest structure. It may thus be a better approach to first carry out small-scale pilot projects in high biomass density regions to ascertain the usefulness of SAR for biomass measurement in such regions. In areas where biomass density is below the saturation threshold, studies already published have established that SAR can give very useful measurements of AGB.

In the specific case of Pakistan, between 1990 and 2010, forests were destroyed at the alarming rate of 27,000 ha per annum, placing Pakistan among the countries with the highest percentage-wise deforestation rates in the world (FAO 2010). Since 2011, Pakistan has become a member of the Reducing Emissions from Deforestation and Forest Degradation (REDD) programme. The global scale AGB density map for Pakistan is shown in Figure 31b. National or local scale AGB maps will be required in the future for accurate MRV as part of the REDD programme; remote-sensing data, especially synergetic use of optical, Lidar, and SAR remote sensing, is ideally suited for this purpose. To the authors' knowledge, there has been no reported study of AGB estimation at the national or local scale in Pakistan. The global-scale map (Figure 31b) indicates that the AGB density may be too high for L-band SAR to be of much use in the northernmost part of the country, but biomass retrievals from SAR can definitely be attempted in other areas.

As mentioned before, L-band spaceborne SAR data will be required for further work on deriving biomass over the HKH and associated regions. Data from the legacy L-band SAR satellites from the Japan Aerospace Exploration Agency (JAXA), JERS-1, and ALOS-1, may be explored to understand the data and delineate areas where biomass estimation may be possible. We further recommend exploring the possibility of more frequent imaging of focus areas through the upcoming ALOS-2 satellite.

Finally, for the data processing approach, we recommend following the recent focus on using reference biomass data in conjunction with models to calibrate SAR backscatter and derive biomass measurements. In fact, independent SAR datasets will not be useful unless reference measurements are available for calibration purposes. Reference biomass data can come from any other source at a comparable scale: optical or infrared satellite measurements, plot surveys, or Lidar campaigns. It is imperative that either reference measurements are already available before acquisition of SAR datasets for biomass estimation in the HKH region, or that measurement campaigns from other methods are conducted in parallel. The exact form of the model and regression methods to be used remains an open question, and will depend on the specific forest type, forest structure, and biomass density in the areas of interest. Other important factors that need to be kept in mind are vegetation water content and soil moisture conditions as these affect L-band backscatter.

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Estimation of Forest Biomass Using the Lidar-Assisted Multi-Source Programme

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L idar (light detection and ranging) is an active remote sensing technology which provides 3D information on terrain and vegetation. In general, Lidar data with a pulse density of ~1 return per square metre are sufficient for forest inventory applications. Vegetation height and density can also be assessed directly from Lidar data, but compared to optical or radar satellite data, this is not efficient when high temporal resolution or very large area mapping is required. The Lidar Assisted Multi-source Program (LAMP) is a forest inventory methodology that integrates Lidar data with satellite data and field data for estimating forest characteristics such as biomass and carbon stocks over large areas. It takes advantage of both the high precision of Lidar and the good temporal and spatial coverage of satellite data. LAMP methodology was applied in three case studies in the tropical countries of Lao PDR, Nepal, and Ghana. Wall-to-wall LAMP biomass estimates were produced for a grid with a cell size of maximum 1 ha and verified against field data. The case studies prove that LAMP is a scalable, fast, robust, and cost-efficient approach for estimating forest carbon and biomass. The results indicate that LAMP methodology is a promising approach for achieving the Tier 3 requirements for REDD+ in monitoring, reporting, and verification (MRV) at national and sub-national scales.

Keywords: light detection and ranging, Lidar, satellite imagery, REDD, Bayesian interpretation, forest inventory

Introduction

Tropical deforestation and forest degradation account for about 15–20% of annual greenhouse gas (GHG) emissions, thus being the second largest source of GHG emissions globally (IPCC 2013). The Reducing Emissions from Deforestation and Forest Degradation (REDD+) scheme may provide sustained incentives for developing countries in the future to reduce emissions from forested lands and invest in sustainable development by providing a financial value for the amount of carbon stored in forests (Angelsen et al. 2009). REDD+ includes the role of forest conservation, sustainable management of forests, and enhancement of forest carbon stocks in the financing mechanism (Angelsen et al. 2011). A successful REDD+ mechanism will require the design and implementation of operational forest monitoring, reporting, and verification systems that are transparent, complete, consistent, comparable, and accurate at national and sub-national scales (Walker et al. 2010; Penman et al. 2003).

An integrated system of unbiased geospatial and statistical estimators of sequestered carbon amounts across forest land is highly important for REDD+. Combining remotely sensed data with a forest resource inventory provides a practical means to generate such information. Remote sensing can be used to collect and interpret information about features from a distant location and obtain continuous data over large areas in the form of continuous thematic maps (e.g., forest biomass). There is a tremendous diversity in the number and properties of sensors and imagery available today, ranging from space-borne to airborne to ground-based systems. Each system has different properties with different spatial resolution, number of spectral and radiometric bands, temporal frequency, and cost of acquisition. Despite this diversity, no current remote sensing system directly measures forest biomass and sequestered carbon. Remote sensing is effective at indicating where specific features are and how they are distributed, but cannot provide an accurate estimate of how much of that feature is in the mapped area without an integrated resource inventory.

In recent years, airborne Lidar has become an integral part of operational forest inventory in Scandinavian countries (Næsset 2007). Its high potential for REDD+ related biomass inventories in tropical countries has been well demonstrated (Asner et al. 2009, Gautam et al. 2010, Asner et al. 2012, Asner et al. 2013, Asner et al. 2014). Vegetation heights can be acquired with high accuracy using Lidar height metrics (Figure 32). Since tree height is strongly correlated with tree volume, forest biomass can be predicted with high accuracy when

Figure 32: **Lidar point cloud cross section and Google map image from the same location (green rectangle) from Savannakhet province, Lao PDR**
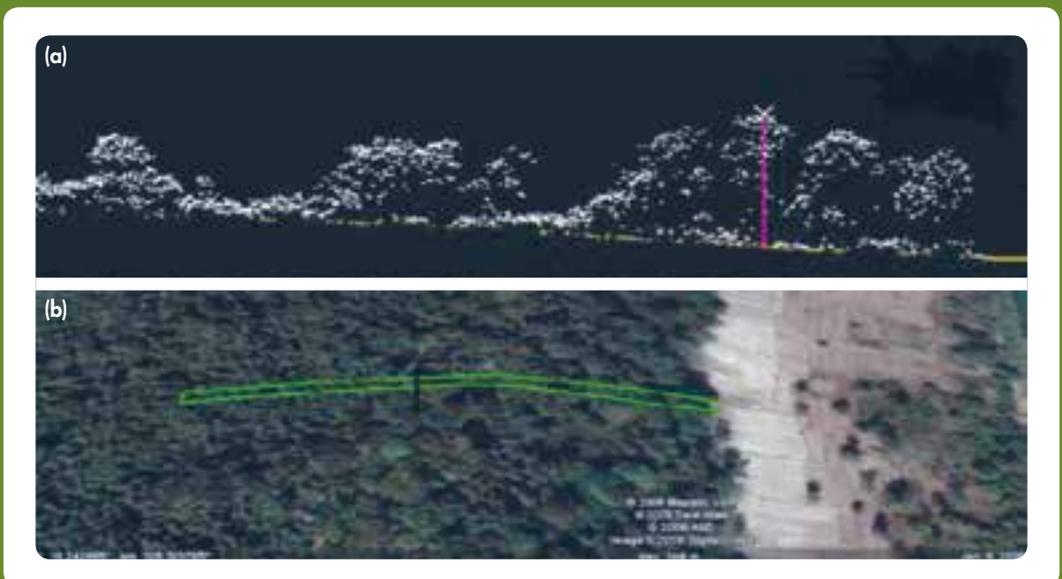
regressing Lidar metrics with data from field measured plots. Wall-to-wall covering of an area of interest with Lidar is relatively expensive, thus a two-phase estimation approach has been proposed which only requires Lidar data from a sample of the study area. This methodology is referred to as the 'Lidar-Assisted Multi-source Programme' (LAMP) and combines Lidar coverage of a sampled sub-area with field plots with wall-to-wall satellite data to develop forest biomass statistics and a biomass map of up to one hectare spatial resolution (Gautam et al. 2010, 2013). The method can be applied to many types of forest when adjusted to local biophysical conditions.

In this paper we review the LAMP method in the context of three different case studies from Lao PDR (Gautam et al. 2010), Nepal (Gautam et al. 2013; Joshi et al. 2014), and Ghana (Sah et al. 2012). First, the general LAMP process is described briefly, the three studies are then presented with the main results, and finally, we discuss the common findings of the case studies.

Methodology

Lidar-Assisted Multi-source Program (LAMP)

The LAMP method follows a two-phase estimation approach. In the first phase, forest variables related to biomass are estimated with high accuracy from Lidar information in selected sample areas where full-coverage Lidar data and data from ground-truth plots are collected. A rectangular sample block or strip sample design is applied to sample Lidar data over the area of interest. The field plots are used as a training dataset for the first-phase of biomass estimation. In the second phase, the highly accurate estimates in the Lidar sample area are used as surrogate plots (simulated field plots) in the interpretation of medium-resolution satellite scenes for the entire study area (Gautam et al. 2010).

LAMP Phase 1: Estimating forest parameters for Lidar coverage area

In the first phase of the LAMP approach, a regression model is generated based on the relationship between the Lidar metrics (height and density) and field measurements. Sparse-Bayesian methods offer a flexible tool for regressing Lidar echo histograms with forest parameters. The Sparse-Bayesian regression method is a robust estimation algorithm that automatically builds an optimal linear regression model for forest parameter estimation and selects predictor variables so that the model remains well-conditioned even when the candidate predictors are highly correlated and when there are not many field plots available for model calibration. While performing comparably to traditional regression methods, they are computationally more efficient and allow better flexibility than step-wise regression (Junttila et al. 2008; Junttila et al. 2010). The Sparse-Bayesian regression model is then applied to predict forest characteristics for a set of thousands of surrogate plots of about one hectare size within the forested area of the Lidar coverage.

LAMP Phase 2: Expanding the estimates to the entire area of interest using satellite data

In the second phase of the LAMP approach, the forest characteristics estimated for the surrogate plots from the Lidar data are applied as simulated ground-truth to generate a regression model between biophysical forest parameters and features derived from satellite imagery. Again, the Sparse-Bayesian method is used to regress satellite-derived variables with the forest characteristics for the locations of the surrogate plots. The satellite-based variables are derived from the satellite data's spectral and textural features and vegetation indices for the area within each surrogate plot and include the means and standard deviations of spectral values in the red, green, and infrared bands, and from the Normalized Difference Vegetation Index, and Haralick texture features from the same bands (Haralick 1979). A subset of the variables is selected for each inventory project using the Sparse-Bayesian method.

In the second phase, it is possible to produce Tier 2 level output for forest classes by using surrogate plot estimates to derive forest class specific estimates for mean and variance. This can be done if the inventory area is classified into meaningful forest classes using, for example, satellite data.

Variance preserving estimates are produced so that the true variance of forest parameters that Lidar models can reproduce is imputed into the satellite-based estimates via histogram matching from the corresponding histogram of the surrogate plots.

The final Tier 3 level output includes biomass and carbon estimates for coarser spatial resolution. The spatial resolution of the Tier 3 level outputs is reduced to one hectare pixel size. The mean value of biomass/carbon calculated from the forest class mean values (Tier 2 level output) and the mean from the Tier 3 level output (one hectare grid) are equal, and both are unbiased estimates of the mean biomass/carbon within the area of interest.

Case studies

The LAMP method was used in three case studies. The main features are described briefly in the following sections. The materials used in each case study are summarized in Table 13.

Lao PDR

The study area was situated in Savannakhet province, Lao PDR. The Lidar survey covered the whole study area, a total of 25,000 ha. The Lidar survey and field campaign were carried out in 2009; the satellite images (ALOS AVNIR-2 and Landsat 7) were from 2006 and 2000, respectively. To test the two-phase LAMP approach, every tenth Lidar flight line (strip) was used as a sample. In order to acquire a plot sample that represents the variation in biomass in the study area well, surrogate plots were placed at random with a probability proportional to the estimated biomass. In all, 90% of the area was interpreted using satellite data with the regression models based on the Lidar estimate of the surrogate plot data (Gautam et al. 2010). Stratification was not applied due to the small study area.

Table 13: **Materials used in the case studies**

	Lao PDR	Nepal	Ghana
Inventory area (km^2)	250	23,300	15,153
Lidar sample area (% of inventory area)	10	5	5
Laser scanner	Leica ALS 40	Leica ALS 50-II	Leica ALS 50-II
Point density (points/m^2)	~1	~0.8	~2.0
Satellite data	Alos AVNIR-2	Landsat 5 TM	Alos AVNIR-2/ DMC
Number of images	1	5	7/1
Field plot type	rectangular	circle	rectangular
Field plot area (m^2)	400	500	400
Number of field plots	328	738	254

Nepal

The study area was located in the Terai Arc Landscape in southern Nepal. The Lidar survey and field campaign were carried out in 2011; the satellite images (five Landsat 5 TM images) were from 2010 and 2011. The applied Lidar sample was a weighted random block sample with a block size of 5 x 10 km. The weights were decided by expert judgement of the variation of forest types. The Lidar sample covered about 5% of the total study area of more than 23,300 km^2. A total of 738 systematically located field plots measured inside the Lidar blocks were used in phase one. The images were radiometrically normalized and mosaiced. In LAMP phase one, biomass models were estimated based on Lidar features and field-measured biomass. In LAMP phase two, the phase one models were used to generate 10,000 surrogate plots of one hectare and the surrogate plot estimates were used to generate the phase two model. The final result was a grid level estimate (cell size 1 ha) for the whole study area (Gautam et al. 2013).

Ghana

The study area was located in western Ghana. The total area was 15,153 km^2 of which 5% was covered with a systematic Lidar strip sample. Seven ALOS AVNIR-2 and one DMC satellite scene were used to produce a land use classification for the study area (Sah et al. 2012). A weighted cluster plot sample of 254 field plots was used to generate phase one regression models for a total of four forest strata (a closed canopy forest model and models for open forests/croplands within wet, moist, and dry zones). In phase two, the phase one models were used to estimate mean and variance for each forest zone using the whole Lidar sampled area. The primary result of the LAMP process in this case was the Tier 2 level output, i.e. Lidar-model derived means and variances for each ecological forest zone.
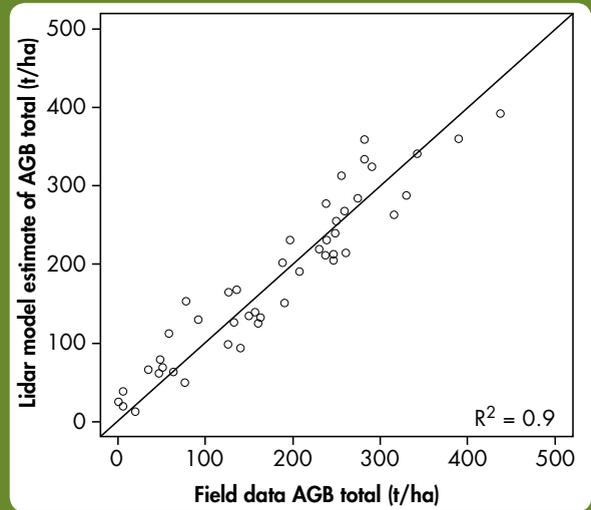
Results

LAMP Phase 1 estimation results

The Phase 1 biomass estimates were validated against field plots. In Lao PDR, the relative root mean square error (RMSE%) for mean above ground biomass (AGB) estimate was 23.3% when the Lidar estimates were validated against the original field plots of size 400 m² (Gautam et al. 2010). In Nepal, the phase one Lidar models were validated against independently sampled larger validation plots of 2,826 m² (Joshi et al. 2014) and the RMSE% was 17.0% (Gautam et al. 2013). In Ghana the Lidar model results were validated in a similar way to those in Lao PDR. In general, the Lidar estimated biomass correlated well with the field measured biomass and there was no saturation effect (Figure 33).

Figure 33: **Scatter plot of the Nepal case study LAMP Phase 1 estimates and field measured values at field plot level**

Source: Joshi et al. 2014

LAMP Phase 2 estimation results

In the Lao PDR and Nepal case studies, in which Tier 3 level outputs were produced, the phase two outputs were validated against Lidar estimates of surrogate plots. In Lao PDR, the RMSE% of the mean AGB estimate was 23.9% at one hectare level (Gautam et al. 2010); in Nepal, the value was 42.1% (Gautam et al. 2013), indicating better estimation results in Lao PDR than in Nepal. The RMSE% values do not include the phase one model bias and may therefore slightly underestimate the true error. Saturation of the satellite image signal is a common problem when optical satellite data are applied in biomass estimation. Comparison of the scatter plots of surrogate plot biomass and LAMP phase two output showed that the satellite signal saturated at about 200 tonnes/ha in the Lao PDR case, whereas no such effect was visible in the Nepal case (Figure 34). The Nepal estimates were produced by imputing the variance of surrogate plots, which eliminates the saturation effect almost completely but increases the RMSE%. In the Ghana study, Tier 2 level output was provided, thus no RMSE% values were available at the one hectare level.

Figure 34: **Scatter plot of the LAMP Phase 2 estimates and surrogate plot Lidar estimates at one hectare level in the Nepal case study**
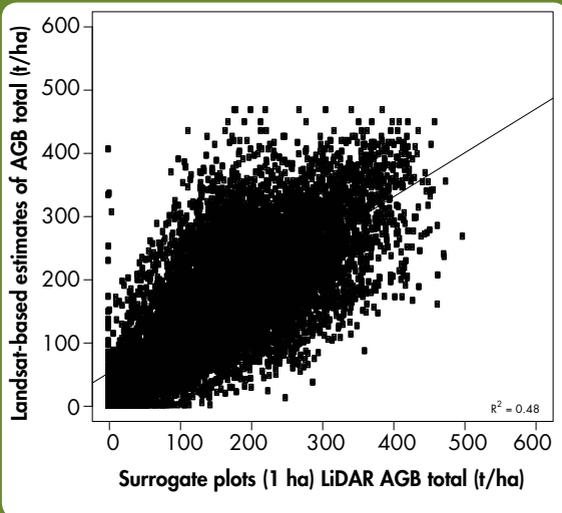
Source: Gautam et al. 2013

Discussion

In the following sections, we present some of the key findings from the three case studies concerning the specifications of the input data materials and the reference data costs.

Field plots

The field plots used in LAMP have requirements for plot positioning and plot size that differ from those of field-based surveys. To overlap field data with Lidar data accurately, the plot positioning error should be minimized and the plot size maximized. The experience from the three case studies showed that the field plots should be positioned with a differentially corrected GNSS (global navigation satellite system) to achieve sub-metre accuracy when the plot size is relatively small. A very dense canopy may obscure the GNSS satellite signal reception completely in dense tropical forests (Nakayama et. al 2014). In this case, it is necessary to perform a bearing and distance measurement between an accurately measured location and the actual plot reference points.

The optimal field plot size is related to the plot positioning accuracy, the spatial pattern of tree locations, and the size of tree crowns. In a field sample, a tree is classified as inside a plot if its trunk centre at a height of 1.3 m is inside the plot. If a tree is close to the plot border, a large part of the crown can be outside the plot but is counted as within. In contrast, Lidar observations for the plot are clipped with a circular cone with exactly the same radius as used for selecting the field trees. Thus, the canopy is presented differently in the field data and the Lidar observations. This border effect increases as an inverse function of plot size and function of mean tree crown size. The spatial pattern of tree locations also affects the estimate; the more clustered the trees are, the more significant the border effect can be. In regular patterns, the effect can also be large if the plot shape and location do not take the spatial trend in forest structure into account, for example the distance between planting rows. In natural tropical forests, the tree crowns can be very large, tree sizes can have a lot of variation, and the spatial pattern is random or clustered. Thus the optimal plot size is usually larger in a natural tropical forest than, for example, in a plantation.

Lidar sample design

Lidar sample design is a trade off between accuracy of the estimates and cost. In the most straightforward approach, the whole area is scanned with wall-to-wall Lidar. Usually, this is not a feasible solution and some kind of sampling strategy should be used; a 2–10% sample rate is sufficient for LAMP. A systematic or random strip sample allows a good representation of the whole area of interest and gives a good starting point for producing unbiased above ground biomass or carbon estimates. However, using strip sampling may give a poor representation of forest types that are present in only a small fraction of the whole inventory area. Block sampling can be more efficient in large and fragmented forest areas, since blocks can be designed so that a large enough sample is collected from each forest type. The cost of Lidar collection is highly dependent on Lidar sample design, thus the sample design should be optimized for each project individually taking into account the representativeness of the sample and other issues while considering the total flight time.

In all three case studies discrete return Lidar was used. There were some indications that if the vegetation structure is very dense the pulse penetration to the ground can be a problem. To provide sufficient ground observations, full waveform Lidar could give more reliable data.

Satellite data

LAMP is not dependent on the particular type of satellite data. The requirements are that the signal in the satellite data should correlate with the biomass or carbon and that the geometric accuracy is good compared to pixel size. Using Lidar estimated surrogate plots allows us to use a large basic estimation unit, for example one hectare pixel size, which is not feasible if field plots are used directly. This feature of LAMP gives an excellent possibility for using low or medium resolution satellite data. The challenge for satellite data application is image normalization without losing the signal. The correlation between the optical satellite data features and the amount of biomass is low compared to the correlation between Lidar features and biomass (see, for example, Figure 33). Further, processing the imagery to render the images spectrally equivalent does not usually improve the correlation.

Reference data cost

Lidar provides a cost-efficient means for acquiring reference data for above ground biomass inventories and distribution mapping. In the field plot based approach, more plots have to be collected to achieve the targeted estimation precision when there is more above ground biomass variation. The cost benefits are highest where the rate of above ground biomass variation within forest strata is high and field measurement costs are higher.

Figures 35a-d illustrate the scale and conditions under which Lidar acquisition with a limited number of field plots (50) per stratum generates cost savings. To provide a realistic view, the sensor and operators are mobilized from abroad in the example calculations, even though local service providers and Lidar data archives are available in many countries. Lidar

coverage of 2% per stratum is expected to be sufficient, and field measurement costs per plot (USD 500–2,500) in the Lidar-assisted and plot-based cases are assumed to be equal. The Lidar acquisition reference costs are modelled based on solicited service provider offers for ten real project cases in Asia (4), Africa (4), and Latin America (2). A power regression model was fitted by applying the total Lidar covered area as the independent variable (hectares) and the Lidar unit cost (USD/hectare) as the dependent variable. The independent variable range was taken from 13,000 to 334,200 ha. The coefficient of determination (R^2) is 0.96 for the resulting Lidar cost model. The Lidar cost model considers mobilization, acquisition, and pre-processing costs.

The scale of operation can have a significant impact on the number of plots required to reach a target precision with a plot-based approach, but that can vary country by country, depending on the degree of spatial variation in forest structure. In our cost comparison figures, the required plot number is kept constant regardless of the scale of operations, while the plot cost is variable (dashed cost lines). This issue can be addressed when adjusting the curves for a specific country case, but requires analysing the available field inventory data.

Figures 35a–d show reference data acquisition costs for Lidar-assisted and plot-based approaches for different scales of operation with different numbers of required plots and different plot costs. The plot-based approach remains more advantageous than the LAMP reference data collection approach, when a field sample of only 100 plots is required to reach the targeted overall precision and the average cost remains below USD 1,000 per plot (Figure 35a). LAMP reference data collection becomes the most cost-efficient approach for an average stratum size of less than 100,000 ha (1,000 km²) when the requirement is for a plot based sample of 250 plots at a cost of USD 500 per plot (Figure 35b); when the scale of

Figure 35: **The scale of operations and reference data acquisition costs for Lidar-assisted and plot-based approaches. The required number of measured plots for the plot-based approach for all scales of operation is taken as a) 100; b) 250; c) 500; d) 1,000 (dashed cost lines)**
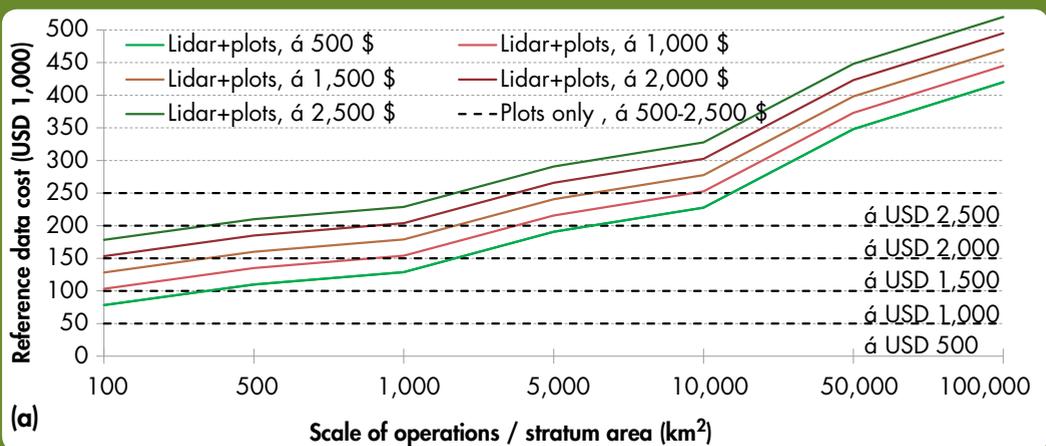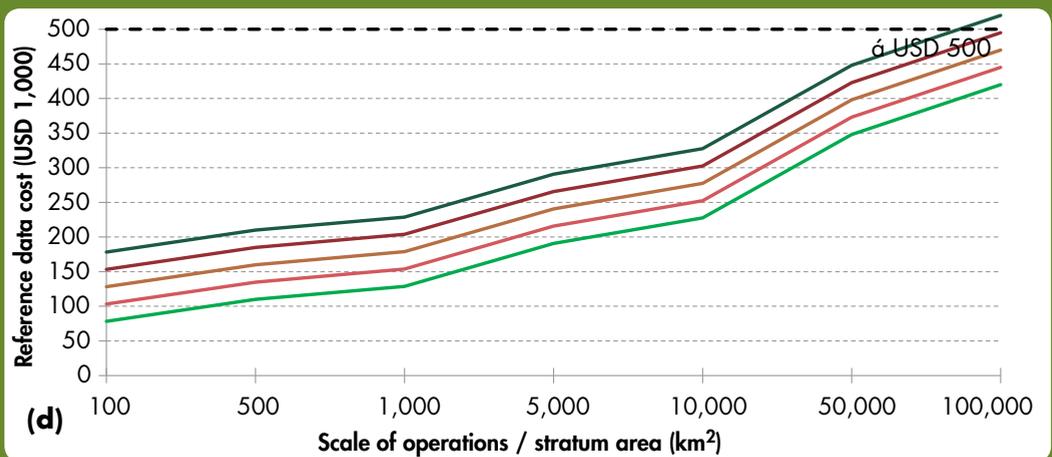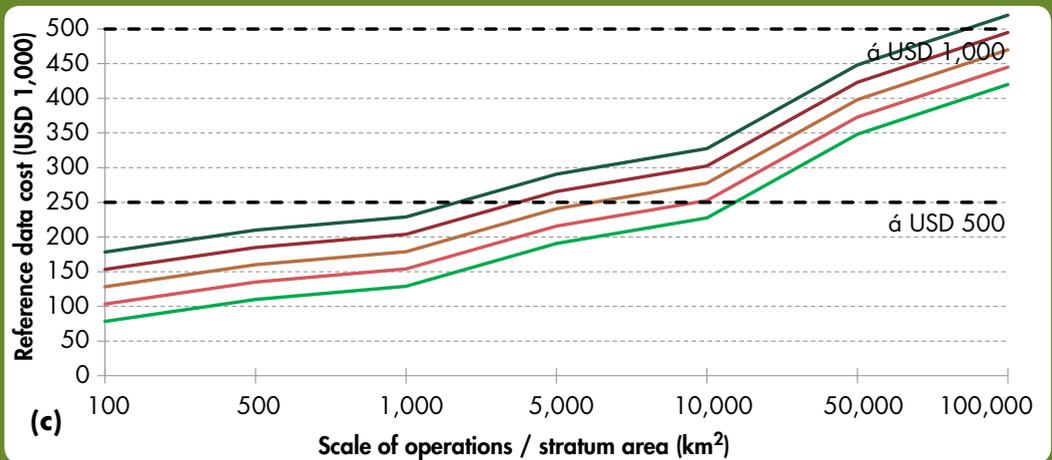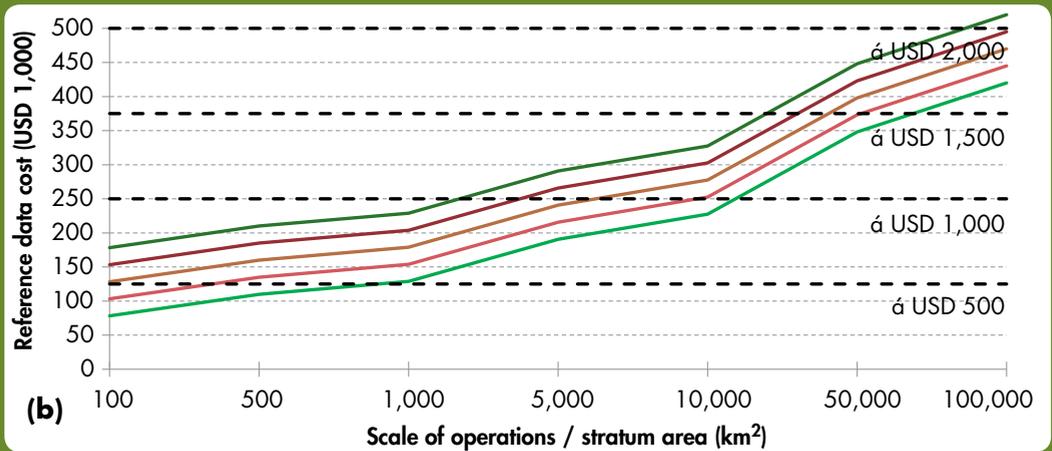
(a)

(b)

(c)

(d)

operations is below 1 million hectares for a plot based sample of 500 plots per stratum at a cost of USD 500 or USD 1,000 per plot (Figure 35c); and under all conditions for a plot based sample of 1,000 or more, even when the average measurement cost remains USD 500 per plot (Figure 35d).

Conclusion

LAMP is an agile, scalable, and reproducible approach for large area biomass and carbon inventories. It can be applied to various forest inventory tasks and it is not dependent on specific input data. However, this gives the user a variety of parameters, which affects the quality of the end result. The reference data costs can be significantly lower and the output data more valuable than in traditional field-based inventories or satellite-based inventories not applying Lidar. LAMP is an example of a multi-source concept. In large scale biomass inventories, multi-source approaches can be effective, since fusing data at different scales provides accurate full coverage results without extensive field measurements.

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Forest Biomass Assessment in Southeastern Bangladesh Using Landsat ETM+ and ALOS PALSAR Data

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S atellite observation of forest cover at local, regional, and global scales is helpful for wall-to-wall forest cover mapping and forest biomass estimation, which contributes to better understanding of the terrestrial carbon flux and global climate change. The objective of the study was to assess above ground forest biomass and carbon stocks in forest ecosystems using Landsat and ALOS PALSAR data together with terrestrial sample based inventory data. The study area was located in southeastern Bangladesh. The area is dominated by tropical moist evergreen and semi-evergreen forest. A Landsat Enhanced Thematic Mapper Plus (ETM+) image from 2001 and Advanced Land Observing Satellite Phased Array L-band Synthetic Aperture Radar (ALOS PALSAR) data from 2007 were used in the study. A forest survey was conducted to measure tree diameter and height by laying sample plots in various forest strata. The measurements were converted to above ground forest biomass using allometric relations and ratios. Forest biomass estimation using optical and radar backscatter was shown to be a challenging task because of the low correlation (r) in regression models. The value of r^2 generally varied between 0.17 and 0.47 for Landsat ETM+ and between 0.17 and 0.50 for ALOS PALSAR. Techniques like the addition of dummy variables in the regression models slightly increased the r^2 value to 0.54 using Landsat data; while normalization of PALSAR backscatter from two different incident angles increased the r^2 value to 0.53.

Keywords: forest biomass, carbon, Landsat ETM+, ALOS PALSAR, regression

Introduction

Periodic monitoring of forest biomass at local, regional, and global scales is essential since the biomass stock in forest ecosystems is changing in different parts of the world. Increases in biomass mean enhanced carbon sequestration and play a role in mitigating global climate change. On the other hand, deforestation and forest degradation release sequestrated carbon to the atmosphere and accelerate the process of global climate change. Forest biomass assessment using terrestrial sample-based forest inventory data is tedious, costly, and time consuming. The technique can function well at a local scale, but at regional and global scales it is extremely difficult to generate a biomass database because of the variability in

forest conditions and biomass levels. However, the approach can be efficient if terrestrial sample based forest inventory can be successfully integrated with remote sensing based biomass assessment. Remote sensing based assessment can provide a wall-to-wall forest biomass map. But the task of successfully combining remote sensing based measurement with ground measured forest biomass data remains challenging.

This article describes a procedure for forest biomass assessment using Landsat Enhanced Thematic Mapper Plus (ETM+) and Advanced Land Observing Satellite Phased Array L-band Synthetic Aperture Radar (ALOS PALSAR) data together with terrestrial sample based forest inventory data. A regression method was used to prepare a forest biomass map for the study area.

Methodology

Study area and datasets

The study area is located in the forests of southern Chittagong in Bangladesh (Figure 36). The forests in the study area are classified as tropical wet evergreen and semi-evergreen (Champion et al. 1965; Figure 37). Dipterocarps are the characteristic feature of the evergreen stratum with some deciduous species from *Anacardiaceous* and *Swintonia* genera also present. Parts of the forests have been deforested or degraded by extreme human interference.

Figure 36: **Location of the study area**
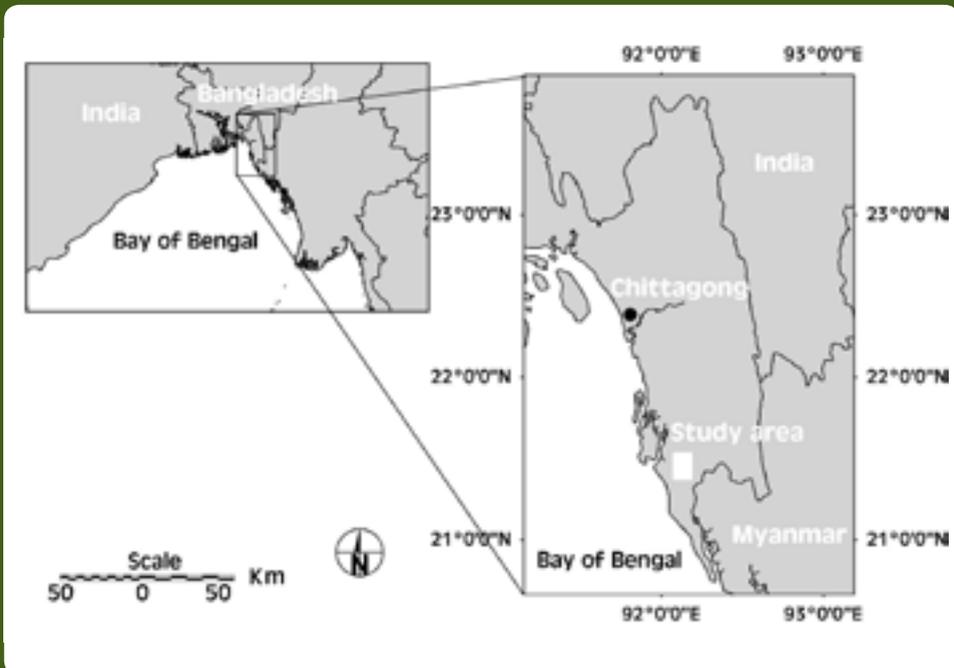
Figure 37: **Tropical wet evergreen and semi-evergreen forests in the study area**

A Landsat ETM+ satellite image from 7 February 2001, and ALOS PALSAR scenes from three different acquisition modes, Fine Beam Single (FBS), Fine Beam Dual (FBD) and PoLaRimetric acquisition mode(PLR), acquired on 13 February, 9 March, and 16 November 2007, respectively, were used in the study. The image acquisition angle for FBS and FBD was 38.78, and for PLR was 23.98.The images were acquired in ascending pass. Data from 100 sample plots were collected from the forests in the study area.

Landsat and PALSAR data processing

The Landsat satellite data were atmospherically corrected using the COST method (Chavez 1996). The COST method is a modified dark object subtraction method where the cosine of the solar zenith angle is taken as the atmospheric transmittance; it is a substantial improvement to the dark object subtraction method. The reflectance of a dark object was taken to be 1% (Moran et al. 1992; Chavez 1996). Landsat digital numbers were converted to at-satellite radiance and finally to surface reflectance.

Level 1.5 PALSAR data were orthorectified with the Shuttle Radar Topographic Mission (SRTM) digital elevation model and PALSAR orbit information obtained from the image header. PALSAR data was further corrected with distributed ground control points taken from the Landsat ETM+ 2001 image. PALSAR digital numbers were converted to Sigma naught (σ^0, in decibels), using Equation 1 (Shimada et al. 2009).

$$\sigma^0 = 10 \log_{10}(DN)^2 + CF \tag{1}$$

Where, CF is the calibration factor (-83.0) obtained from the image header.

The normalized backscattering coefficient (normalized radar cross section; NRCS) was computed using a 7×7 mean spatial filter.

Forest biomass measurement

Terrestrial sample based forest inventory was conducted from late 2001 to early 2004 in the forests of the study area. One hundred temporary sample plots with sizes ranging from 25 to 900 m^2 were surveyed (Table 14). Eight different vegetation types were recognized in the satellite image and sample size varied depending on the vegetation types and characteristics. Sample size was determined based on the results of the previous inventories conducted in the region.

Tree-diameter at breast height (DBH) was measured for all trees exceeding 5 cm DBH inside the sample plots. The height of the three to five dominant trees inside the plot was measured and the height of the remaining trees estimated from these measurements. Trees less than 5 cm in diameter were measured in sub-sample plots of 2×2 m usually laid in the centre of the sample plot. The estimate from the sub-sample was normalized to the standard sampling unit. From the 100 terrestrial samples analysed in the study, 70 samples were chosen at random to develop a forest biomass model, while the remaining 30 samples were used for validation purposes. The validation results are only presented for the ALOS PALSAR data.

Regression analysis

The reflectance values acquired by Landsat ETM+ at different spectral bands and forest biomass were modelled with different forms of regression equations, i.e., linear, logarithmic, inverse, and exponential. Individual band reflectance and the various dummy variables assigned for different forest types were taken as independent variables, and the forest biomass as the dependent variable, in multiple regression models.

Dummy variables are usually unrelated to the physical levels that might exist in the factors themselves (Draper and Smith 1998). If two forest types (type A and B) that produce different response levels (reflectance acquired by satellite sensor data) are included as independent variables in a regression model, a dummy variable, Z, can be added into the model with a regression coefficient, a, so that an additional term aZ appears in the equation. Values can be assigned to Z as follows: $Z=0$, if the observation is from forest type A, and $Z=1$, if the observation is from forest type B (Rahman et al. 2008). Draper and Smith (1998) described the use of dummy variables in regression analysis.

Table 14: **Vegetation characteristics and distribution of ground samples**

Vegetation type	Number of plots	Plot size (m²)	Vegetation structure and characteristics	
			Structural attributes	Dominant species
Natural vegetation				
Primary forest	16	30×30	• Natural origin, multi-storied, a number of mature trees in upper canopy, shrubs and sometimes bamboo in lower canopy, rich in biodiversity • Tree canopy is approximately 10–20 m high in logged-over forest and 20–28 m in well-stocked forest	*Dipterocarpus turbinatus, D. alatus, Syzigium grande, S. wallichi, Swintonia floribunda*
Secondary forest	10	10×10	• The succession stage following earlier disturbance; the trees are younger and smaller than in the primary forest • The forest has a uniform canopy with a height of approximately 5–12 m	*Dipterocarpusturbinatus, D. alatus, Syzigiumgrande*
Bamboo	10	5×5	• Dominated by bamboo, occasionally some scattered trees in the upper canopy • Bamboo is a monocotyledon with a different structure to broadleaved trees. It grows with a single straight stem; small branches with leaves develop from the stem	*Melocanna baccifera* is commonly seen on hilltops and mid-slope; *Bambusa tulda* in the foothills and valleys
Shrubs	11	5×5	• Shrubs intermixed with seedlings and saplings of tree species, bamboo, and grasses • Vegetation in this formation is usually 1–2 m in height	Mixed species
Plantation				
Indigenous species	1 8	10×10 (young plantation) 15×15 (old plantation)	• Monoculture with various indigenous species; the branching patterns of different species are different • Heights of the plantations are variable due to difference in species, age, and site quality	*Dipterocarpus turbinatus, Syzygium grande, Artorcarpus chaplasha, Hopea odorata*
Teak	9 3	10×10 (teak coppice) 15×15(teak plantation)	• Teak has identical large leaves; no other tree species, undergrowth, or ground vegetation is seen in these plantations • Coppice appears in places when parent trees are removed	*Tectona grandis* or coppice
Acacia	10	10×10	• There is a thick layer of green canopy • The heights of plantations are variable mainly because of the difference in age class	*Acacia auriculiformis, A. mangium*
Rubber	12	10×10	• A managed and cultivated ecosystem; the undergrowth is very sparse due to intense weeding operations • Generally, trees are planted with a wider spacing than in other plantations	*Hevea brasiliensis*
Total	**100**			

Adapted from Rahman et al. 2008; Rahman and Sumantyo 2013

The PALSAR response to forest biomass was modelled using the following regression equation (Equation 2):

$$Y = b_0 + b_1(X) \tag{2}$$

Where, X is above ground forest biomass in Mg ha^{-1}, Y is the PALSAR backscattering coefficient (in dB), b_0 is the intercept, and b_1 is the slope of the regression line. The value of b_0 and b_1 can be used to check whether the fitted regression line is similar to the scatter plot data used in building the regression model. They can be used as criteria for choosing a regression model, particularly if several models appear with a similar value of r^2.

PALSAR backscatter from different observation modes (and incidence angles) was normalized using Equation 3.

$$\text{Average backscatter} = (BC_1 + BC_2 + \dots + BC_n)/n \tag{3}$$

Where, BC_1, BC_2, and BC_n are the backscattering coefficients of channels 1, 2, and n, obtained from different incidence angles, respectively.

Results and Discussion

Landsat ETM+ derived forest biomass

The results of the regression analysis show a low correlation (r) in the Landsat ETM+ derived forest biomass model (Table 15). The value of r^2 varies from 0.019 to 0.47.

The value of r^2 increased in the regression analysis when dummy variables were added as independent variables (Table 16). Dummy variables were assigned for different forest types (Table 17). Assignment of different sets of dummy variables produced different intercepts in the regression equation when keeping the same regression coefficient.

ALOS PALSAR derived forest biomass

The coefficients of determination (r^2) obtained from regression analysis for the ALOS PALSAR dataset are presented in Table 18 and Figure 38. The validation result is presented for a low biomass level (0–150 Mg ha^{-1}) and high biomass level (0–423 Mg ha^{-1}) calculated using the selected regression model (Table 19). The value of r^2 increases slightly if the PALSAR data are normalized. The PALSAR derived forest biomass map for the study area is presented in Figure 39. The model derived for an average PALSAR backscatter value of HH and HV (marked * in Table 18), was used to prepare the forest biomass map. Different ranges of forest biomass are shown in different colours. The area estimate of forest biomass presented in the map is shown in Table 20.

Table 15: **Coefficient of determination (r^2) computed for the Landsat ETM+ derived forest biomass model using different optical bands**

Variable	Type of regression equation			
	Linear	Logarithmic	Inverse	Exponential*
Band 1	0.167	0.152	0.134	0.337
Band 2	0.264	0.236	0.198	0.473
Band 3	0.241	0.220	0.186	0.380
Band 4	0.025	0.023	0.019	0.036
Band 5	0.226	0.193	0.141	0.313
Band 7	0.242	0.224	0.180	0.332

Adapted from Rahman et al. 2008
* r^2 computed in a log-transformed model is not comparable with non-transformed models (Parresol 1999)

Table 16: **Coefficient of determination (r^2) computed for the Landsat derived forest biomass model using dummy variables**

Independent variables	Multiple coefficient of determination (r^2)
B1, B2, B3, B4, B5, B7, Z1, Z2, Z3, Z4, Z5, Z6, Z7	0.542
B2, B3, B4, B5, B7, Z1, Z2, Z3, Z4, Z5, Z6, Z7	0.542
B2, B3, B4, B5, Z1, Z2, Z3, Z4, Z5, Z6, Z7	0.542
B2, B3, B4, Z1, Z2, Z3, Z4, Z5, Z6, Z7	0.542
B2, B4, Z1, Z2, Z3, Z4, Z5, Z6, Z7	0.541
B2, Z1, Z2, Z3, Z4, Z5, Z6, Z7	0.539
B2, Z1, Z2, Z3, Z4, Z5, Z6	0.538
B2, Z1, Z3, Z4, Z5, Z6	0.532
B2, Z1, Z3, Z4, Z6	0.515

Adapted from Rahman et al. 2008
B1: Landsat ETM+ Band 1, etc.
Z1 etc.: value of dummy variables (Table 17)

Table 17: **Coefficients of dummy variables**

Vegetation types	Z1	Z2	Z3	Z4	Z5	Z6	Z7
Acacia	1	1	1	1	1	1	1
Bamboo	0	1	1	1	1	1	1
Plantation of indigenous species	0	0	1	1	1	1	1
Primary forest	0	0	0	1	1	1	1
Rubber	0	0	0	0	1	1	1
Shrubs	0	0	0	0	0	1	1
Teak	0	0	0	0	0	0	1
Secondary forest	0	0	0	0	0	0	0

Table 18: **Regression statistics and biomass estimation performance of ALOS PALSAR data**

Data type	Polarization	Model formulation		
		Regression coefficients		r^2
		b_0	b_1	
FBS	HH	-15.037	1.084	0.499
FBD	HH	-11.720	0.699	0.289
	HV	-23.856	1.249	0.190
PLR	HH	-12.432	1.095	0.173
	HV	-21.723	1.377	0.499
	VH	-22.084	1.404	0.499
	VV	-12.981	0.886	0.398
Average backscatter (FBS and PLR)	HH HH	-13.735	1.0891	0.352
	HH HV*	-18.380	1.2301	0.533
	HH VH	-18.561	1.2438	0.532
	HH VV	-14.009	0.9849	0.507

Rahman and Sumantyo 2013
*Model used to prepare the forest biomass map (Figure 38)

Table 19: **Validation results for the PALSAR derived forest biomass model**

Data type	Polarization	Validation	
		RMSE (Mg ha^{-1})	
		Limit 0–423	Limit 0–150
FBS	HH	161	62
FBD	HH	169	69
	HV	205	78
PLR	HH	140	53
	HV	180	65
	VH	176	67
	VV	173	54
Average backscatter (FBS and PLR)	HH HH	151	44
	HH HV	175	63
	HH VH	174	63
	HH VV	163	57

Rahman and Sumantyo 2013
Note: The limit in RMSE computation means that the result is only valid within this range. If a model computed higher than the range of the last limit, the highest value (150 or 423) was taken as the estimated biomass in the computation procedure.

Figure 38: **PALSAR backscattering coefficient plotted against forest biomass (n = 70) and fitted models; the response of PALSAR backscatter on biomass for different forest categories is shown by different symbols**
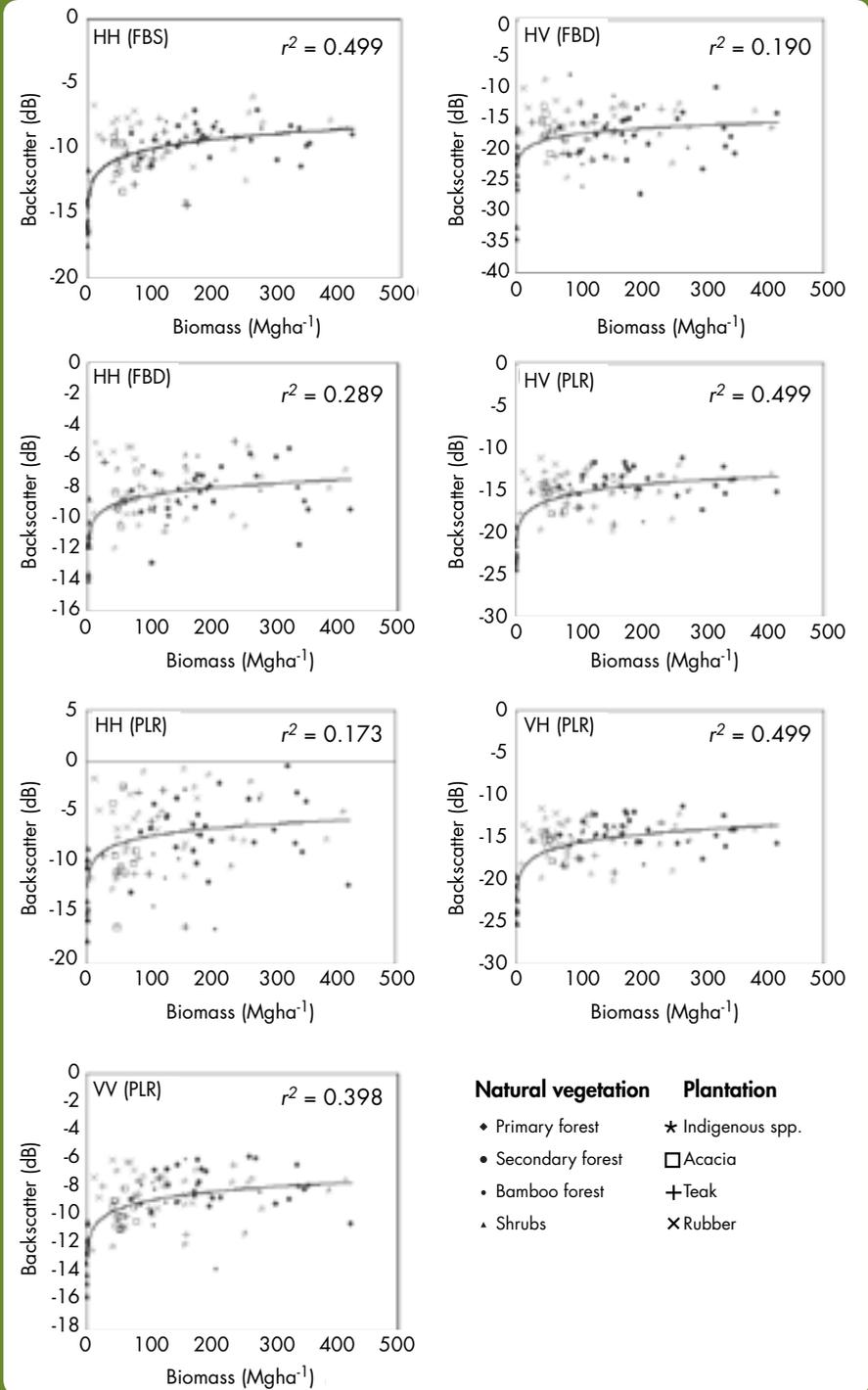
Source: Rahman and Sumantyo 2013

Figure 39: **Forest biomass map of the study area derived from ALOS PALSAR data (2007). Forest biomass was computed using the average backscatter of HH (FBS) and HV (PLR) PALSAR scenes; non-forest was excluded (shown in white)**
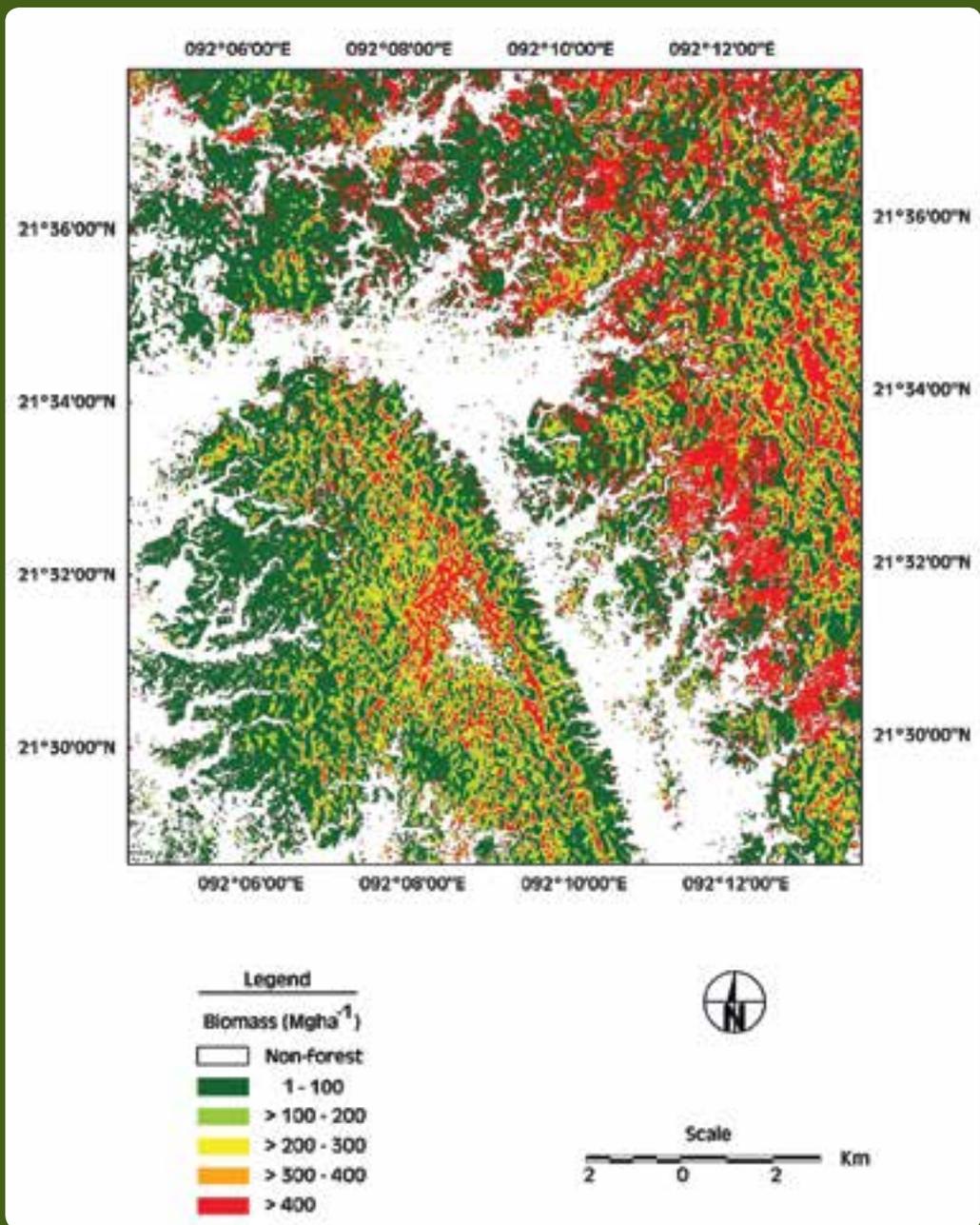
Conclusion

The results indicate the following.

- Forest biomass estimation using optical and radar backscatter is a challenging task because of the low correlation (r) between forest biomass and satellite derived reflectance or SAR backscattering coefficient. The value of r^2 generally varied between 0.17 and 0.47 for Landsat ETM+ and between 0.17 and 0.50 for ALOS PALSAR.
- The low correlation could be the result of signal saturation for the optical and microwave images at a certain biomass level. Moreover, the diversity of the tropical forest ecosystem is high. Satellite reflectance and SAR backscattering coefficients are not only affected by the plants containing the major amount of biomass, but also by other understory and scrubby vegetation layers in the ecosystem.
- Advanced techniques like addition of dummy variables and normalization of SAR backscattering coefficients from various incidence angles slightly increased the coefficient of determination (r^2) in the regression models.

Further study should concentrate on the inclusion of datasets with a higher spatial resolution, and use of interferometric SAR and Lidar data to examine whether the precision in biomass modelling can be increased.

Table 20: **Forest biomass and area estimate of the map**

Biomass level (Mg ha^{-1})	Area (ha)
Non-forest (including biomass less than^{-1})	11,425
1–100	10,397
>100–200	2,712
>200–300	1,326
>300–400	739
>400–423	4,589
Total	**31,188**

Acknowledgements

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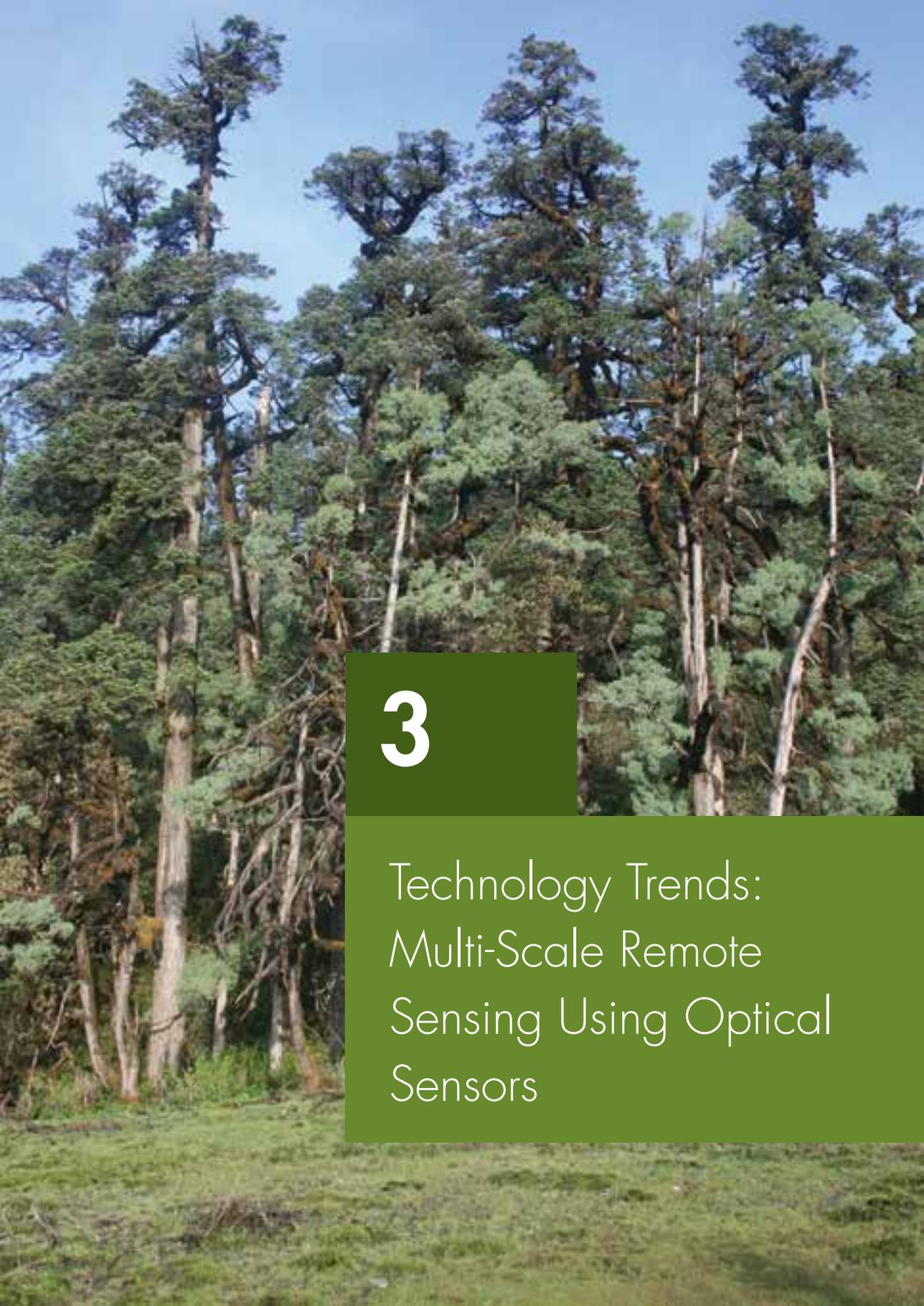
3

Technology Trends:
Multi-Scale Remote
Sensing Using Optical
Sensors

Spatial Distribution of Biomass in Indian Forests Using Spectral Modelling

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This paper presents spatial estimates of the above ground phytomass density for temperate, tropical, and deciduous forests in three states of India – Sikkim, Tamil Nadu, and Madhya Pradesh – using a spectral modelling method applied to MODIS (250 m spatial resolution) satellite data from 2010. Phytomass density was estimated using inventory data collected in 2009/10 as part of a larger national effort, the ISRO GBP National Carbon Project, and organized in a geographic information system. Tree level measurements were converted to phytomass density using region and species specific volume equations (from the Forest Survey of India), biomass expansion factors, and wood specific density. In addition, diameter/girth and height and their relationship with tree volume/biomass were used to assess plot biomass. The phytomass density at site level ranged from 11.66 to 256.09 t ha^{-1}, with an average of 93.07 t ha^{-1}, for temperate forest (Sikkim); from 31.66 to 308.53 t ha^{-1}, with an average of 160.36 t ha^{-1}, for tropical forest (Tamil Nadu); and from 2.2 to 146.14 t ha^{-1}, with an average of 53.38 t ha^{-1}, for deciduous forest (Madhya Pradesh). We discuss the utility of spectral models for regionalizing field inventory data and for a nationwide effort. We also attempt to assess the uncertainties in above ground biomass estimates (AGB) and examine 1) error due to tree measurement, 2) error due to choice of allometric model relating AGB to other tree parameters, 3) sampling uncertainty related to the size of the study plot, 4) representativeness of a network of small plots over a large forest area, and 5) spatial uncertainty related to the geographic location of the study plot.

Keywords: forestry, forest inventory, allometric equation, above ground biomass (AGB), carbon stock, spectral model, uncertainty

Introduction

Forests contain about 80% of global terrestrial above ground carbon stocks and play an important role in the global carbon cycle (Houghton 2005). Tropical forests are important carbon-pools comprising approximately 40% of terrestrial carbon storage (Dixon et al. 1994) and they support a large stock of carbon in the form of biomass, but release more CO_2 when disturbed (Palm et al. 1986). Tropical deforestation contributes about one-fifth of total

anthropogenic CO_2 emissions to the atmosphere (Houghton 2007). In order to obtain accurate estimates of carbon flux, it is necessary to know the actual biomass of degraded and logged forest, rather than use values averaged over large regions (Houghton 2005). The quantity of biomass carbon in a given ecosystem is one of the most uncertain factors involved in estimating changes in carbon flux from terrestrial ecosystems (Brown et al. 1989). Accurate estimates of carbon flux require improved knowledge of the density and spatial distribution of forest biomass across the globe, particularly in high biomass tropical forest ecosystems. Indian forests are a major tropical forest ecosystem constituting nearly 69.20 million hectares, 21.1% of the geographical area of country (FSI 2011). India's geographical area constitutes 2.4% of the world's land area and about 2% of the global forests, while supporting 16% of the world's human population. Indian forests are known to be one of the richest in terms of vegetation types and species diversity.

There are three main approaches to biomass assessment: field measurements, remote sensing (RS), and geographic information systems (GIS) (Lu 2006). Field measurement is often considered the most accurate, but is costly and time consuming. Although field inventories are an efficient way of assessing carbon stock, it is essential to address uncertainties associated with above ground biomass (AGB) estimates. There are many sources of error which can affect the estimation of forest biomass: a) sampling error; b) measurement error related to the tree variables, such as DBH (diameter at breast height), height, and weight; and c) error due to the choice of model to relate biomass to the tree variables. Chave et al. (2004) reported uncertainty on the AGB estimation of a single tree of diameter 10 cm or greater as 47% of the estimated AGB, 31% due to the allometric model and 16% due to the measurement uncertainty. These uncertainties are greater for tree level AGB estimation; the errors average out at stand level.

Modern tools like remote sensing and GIS have provided new opportunities for quick and reliable assessments and for monitoring of AGB and carbon pools. Many studies have been carried out in recent years for biomass estimations of Indian forests, but there have been fewer efforts to take full advantage of high temporal resolution remote sensing data in assessing vegetation carbon pools.

The carbon stock in Indian forests has been estimated based on growing stock volume data of forest inventories and using appropriate conversion factors for both biomass and carbon (Ravindranath 1997; Lal and Singh 2000; Chhabra et al. 2002; Dadhwal et al. 2009). Dadhwal and Shah (1997) used state-wise remote sensing based forest area, field inventory based growing stock, and crown density based biomass expansion factor to derive the phytomass carbon pool (4,017 Tg C) and phytomass carbon density (63.6 Mg C ha^{-1}) for India's forests. Using a similar approach, Chhabra et al. (2002) estimated the forest phytomass carbon pool of the entire country as 3,871.2 in 1988 and 3,874.3 Tg C in 1994. Earlier studies show that vegetation indices, particularly NDVI, are good indicators of leaf area index (LAI), and are positively correlated with biomass and productivity (de Fries et al.

1995; Kale et al. 2001; Madugundu et al. 2008; Roy and Ravan 1996). Madugundu et al. (2008) used IRS P6 LISS-IV satellite data for AGB estimation in deciduous forests in the Western Ghats of Karnataka. A regression model based on NDVI and field measured LAI ($r^2 = 0.68$, P ≤ 0.05) were used to generate a remote sensing based LAI. A regression model was developed between LAI and field measured AGB ($r^2 = 0.63$, P ≤ 0.05) to generate the spatial distribution of AGB in the region.

Keeping in view the importance of AGB estimation and its spatial distribution, this study discusses the utility of spectral models for regionalizing field inventory data for different forest types. We also attempt to assess the uncertainty in AGB estimates and examine 1) the error due to tree measurement, 2) the error due to the choice of allometric model to relate AGB to other tree parameters, 3) sampling uncertainty related to the size of the study plot, 4) representativeness of a network of small plots over a large forest area, and 5) spatial uncertainty related to the geographic location of the study plot.

Methodology

Study area

Spatial estimates of phytomass density were developed for temperate, tropical, and deciduous forests. The three different vegetation types were covered in three states of India – Sikkim, Tamil Nadu, and Madhya Pradesh (Figure 40). A total forest area of 3,003 km² was covered in Sikkim, mainly Himalayan Moist Temperate (1,775 km²) and Montane Wet Temperate (1,139 km²); 4,831 km² forest in Tamil Nadu, dominated by Dry Deciduous (1,887 km²), Moist Deciduous (1,631 km²), Evergreen (718 km²), and Semi-evergreen (517 km²); and 21,915 km² forest in Madhya Pradesh, mainly Dry Deciduous (10,100 km², close to 50%), Teak (7,394 km²), Moist Deciduous (3,262 km²), and Sal (958 km²).

Field sampling

Field inventory data collected in 2009/10 as part of a larger national effort, the ISRO GBP National Carbon Project (Dadhwal et al. 2011), were used in the present study. The National Carbon Project employed a common inventory design for the entire country. Satellite data (IRS AWiFS) from 2007/08 and ancillary maps available from ISRO/DOS and the Forest Survey of India (FSI) were used to design the sampling strategy. The country was divided into 20 zones (corresponding to AWiFS scenes) representative of the different bio-geographical and agro-climatic zones. A total of 125 sample sites were randomly selected for the inventory in each zone based on the type and density of the forest/vegetation. The sample sites were 250 x 250 m, the size was chosen to be usable with MODIS and AWiFS satellite data. Four sample plots of 0.1 ha each were laid out at each sample site. The design ensured adequate coverage of all major forest types and forest density classes in the different ecoregions. In total, about 10,000 sample plots at 2,500 sample sites were identified for ground observations in forest ecosystems, equivalent to a sampling intensity of 0.0015% in the forest ecosystem at country level.

Figure 40: **Study area**
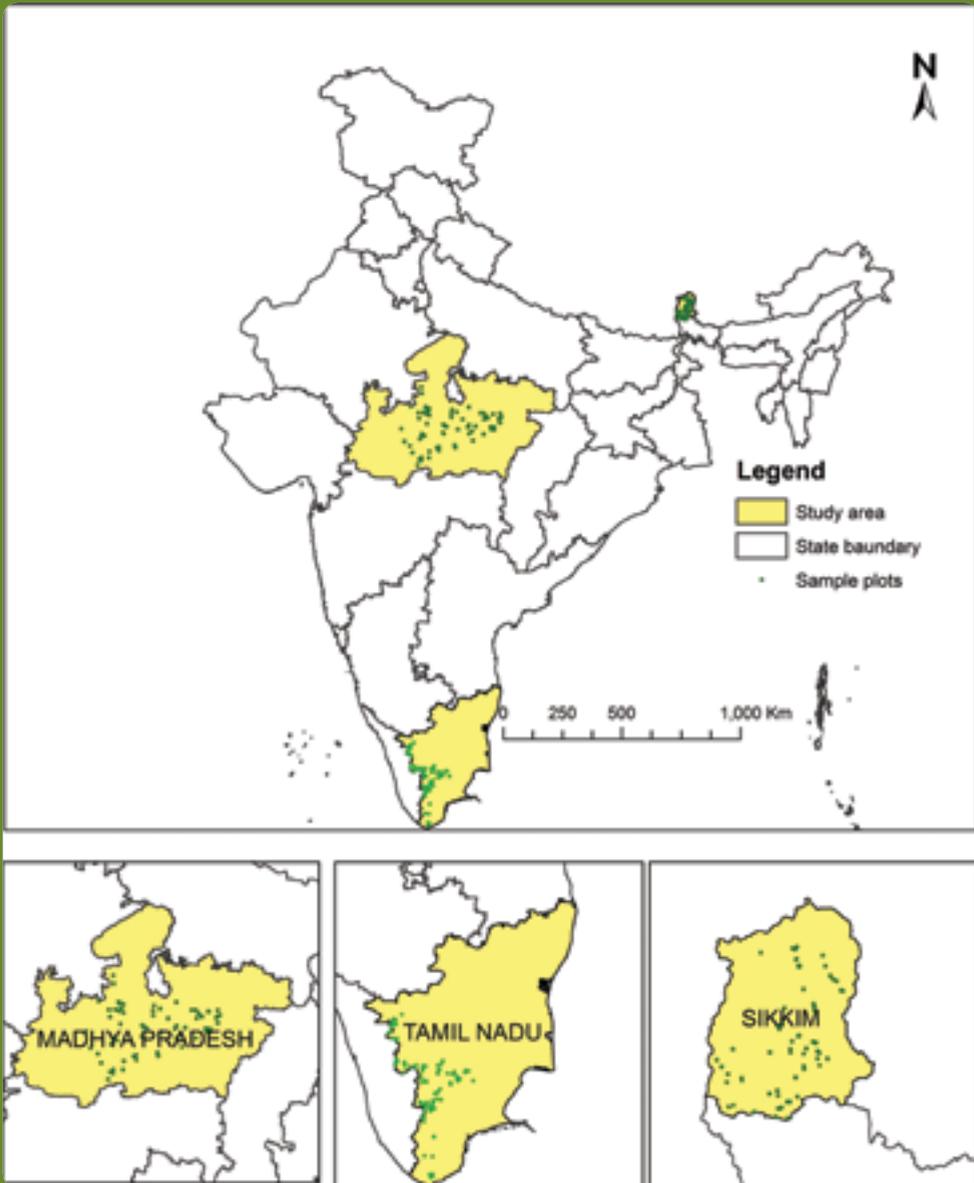
The clustered sampling approach using four 0.1 ha plots at each sample site provides better biomass average values and improves the correlation between biomass and satellite data during spectral modelling. Diameter at breast height (1.3 m above the ground) and height were measured with a measuring tape and hypsometer for all trees with DBH>10 cm. Coordinates of all plots were recorded using GPS. The present study used the ground inventory data from 28, 32, and 50 sample sites in Sikkim, Madhya Pradesh, and Tamil Nadu, respectively.

Data processing

The field inventory data were organized in a geographic information system. Tree level measurements were converted to phytomass density using region and species specific volume equations (FSI 1996), biomass expansion factors, and wood specific density. In addition, individual tree level parameters – diameter/girth and height – and their relationship with tree volume/biomass were used to assess plot biomass.

Area weighted biomass was calculated from the actual forest area within the sample site (derived from satellite data) multiplied by the average biomass of the sample plots within the site (from the field inventory). The steps followed in the area weighted biomass estimation are shown in Figure 41. The area weighted biomass was regressed with satellite derived parameters, and a best fit regression equation was used to map the spatial distribution of AGB. The area weighted biomass was used in the regression instead of the average site biomass to exclude any contribution from non-forest classes. Non-forest classes were given zero weight in the weighted area biomass estimation.

Figure 41: **Area weighted biomass estimation**
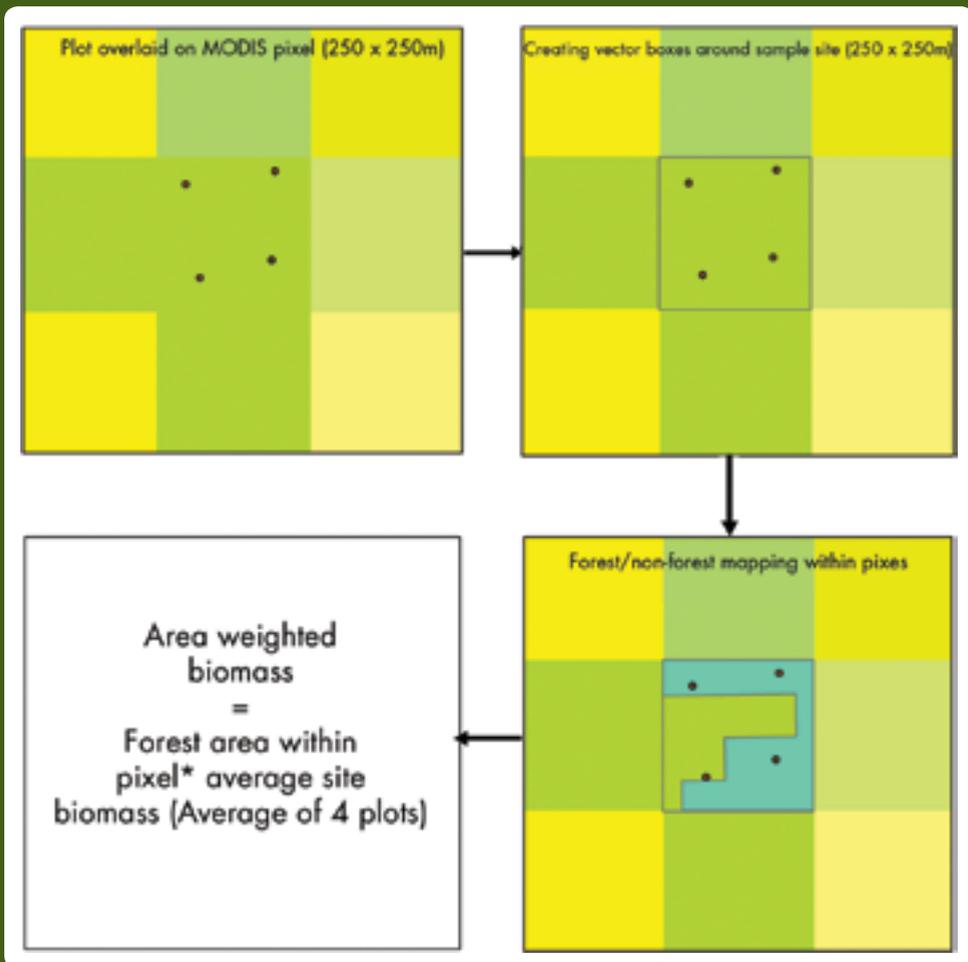
Results and Discussion

Allometric equations (see below), wood density, and expansion factors were used to estimate species biomass from the inventory data. The field measured phytomass density for individual plots for temperate forests ranged from 11.23 to 425.04 t ha^{-1}, with an average of 93.07 t ha^{-1}, while for tropical forests phytomass density ranged from 30.89 to 495.98 t ha^{-1}, with an average of 160.36 t ha^{-1}. Phytomass density for deciduous forest ranged from 0.97 to 221.34 t ha^{-1} with an average of 53.38 t ha^{-1}. The wide variation in AGB in individual plots is the result of variation in species composition, age, tree density, and basal area (tree size) of trees within plots. The mean site biomass (averaged from the four inventory points at each site) was11.66 to 256.09 t ha^{-1} for Sikkim, 2.20 to 146.14 t ha^{-1} for MP, and 31.66 to 308.53 t ha^{-1} for Tamil Nadu.

The plot level biomass values were used to calculate area weighted biomass.

Regression analysis

The area weighted biomass ranged from 5.49 to 178.33 t ha^{-1} for temperate forest, 2.53 to 148.21 t ha^{-1} for tropical forest, and 7.00 to 111.39 t ha^{-1} for deciduous forest.

Multi season MODIS images (February, May, October, and December; year 2010) were used to establish the regression between area weighted biomass and the satellite derived parameter Normalized Difference Vegetation Index (NDVI) for spectral modelling. Multi season MODIS imagery was used because remote sensing data are very sensitive to season, tree phenological characteristics, and degree of crown closure. A significant correlation was observed between the area weighted biomass and spectral responses of different bands and indices.

The area weighted biomass was significantly correlated with NDVI in all three study regions. NDVI is a simple spectral index which can be used to assess whether the target area being observed contains live green vegetation or not. NDVI is calculated from the visible and near-infrared light reflected by vegetation. Healthy vegetation absorbs most of the visible light that hits it, and reflects a large portion of the near-infrared light. Nearly all satellite vegetation indices use the difference formula (Equation 1) to quantify the density of plant growth on earth. Calculations of NDVI for a given pixel results in a number that ranges from minus one (-1) to plus one (+1); no green leaves give a value close to zero. A zero means no vegetation while close to +1 (0.8–0.9) indicates the highest possible density of green leaves.

$$NDVI = (NIR - VIS)/(NIR + VIS) \hspace{3cm} (1)$$

NIR and VIS stand for the spectral reflectance measurements acquired in the near-infrared and visible (red) regions, respectively.

Best fit models for each study area are presented in Figures 42, 43, and 44. The regression equations used for spectral modelling in temperate, deciduous, and tropical forests are given in Equations 2, 3, and 4.

AGB = 305.9x4.864, R^2 = 0.787, n = 28 .....(2)
SD = 189.43   SE = 35.80
where x = December NDVI

AGB = 360.3x2.836, R^2 = 0.721, n = 32 .... (3)
SD = 93.09   SE = 16.45
where x = February NDVI

AGB = 0.387e7.000x, R^2 = 0.735, n = 50 .. (4)
SD = 23.16   SE = 3.27
where, x = February NDVI

The spectral model for Sikkim gave a comparatively higher standard error due to the high variability in AGB. The spectral model for Madhya Pradesh gave a low standard error due to the low variability in AGB of deciduous forests. The standard error was lowest in the Tamil Nadu spectral model because of the higher sampling intensity (large number of sample sites).

The spatial estimates of biomass are presented in Figures 45, 46, and 47. The model estimated total AGB for the three study areas was 18.49, 31.33, and 84.78 million tonnes, respectively. The mean AGB density was estimated to be 71.57, 64.86, and 38.68 t ha-1 for temperate, tropical, and deciduous forest, respectively. These results are consistent with the available biomass estimates for different forest types in India. Chaturvedi et al. (2011) reported

Figure 42: **Regression analysis for Sikkim state (December NDVI and biomass)**
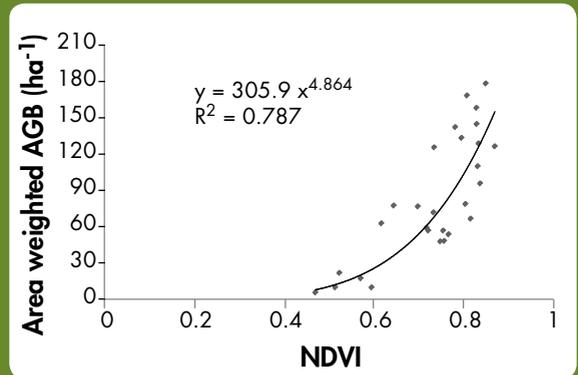
Figure 43: **Regression analysis for Madhya Pradesh (February NDVI and biomass)**
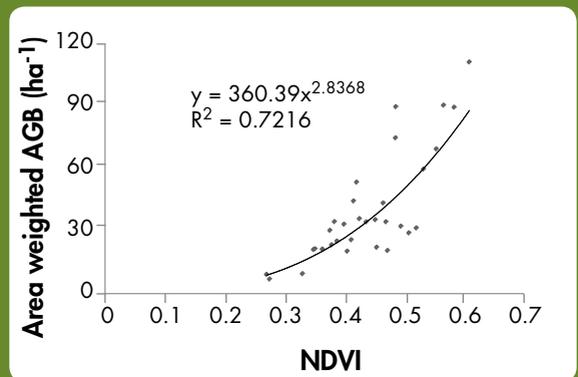
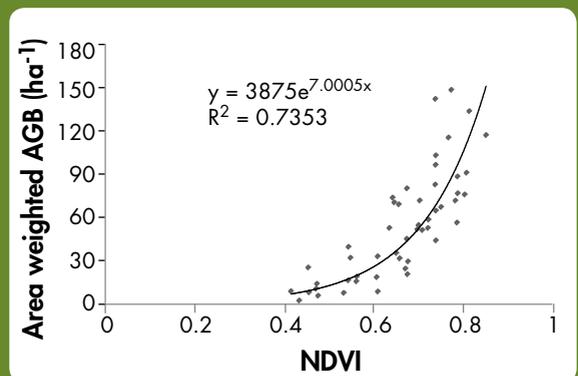Figure 44: **Regression analysis for Tamil Nadu (February NDVI and biomass)**

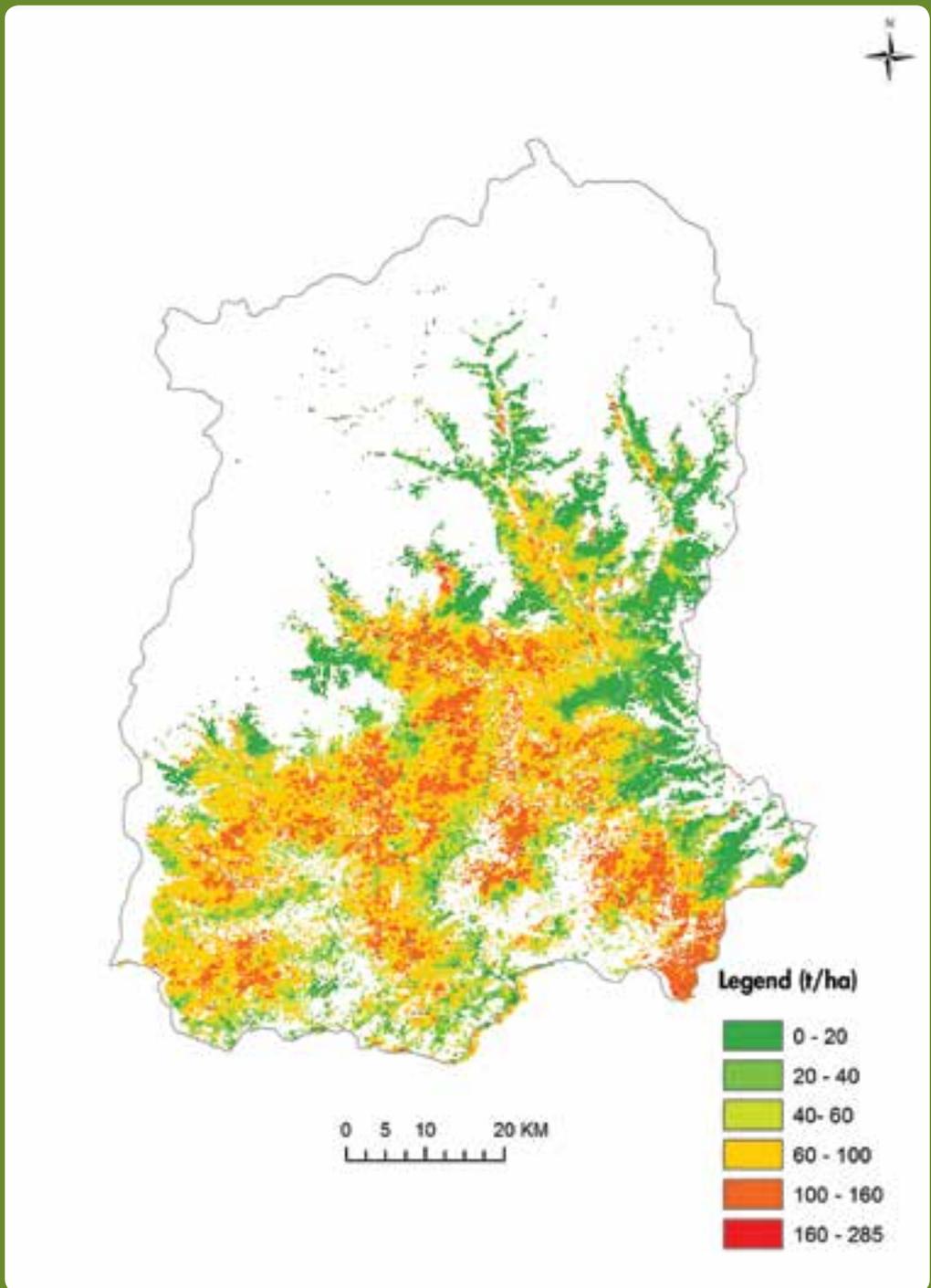Figure 45: **Predicted biomass in Sikkim (temperate forest)**

Legend (t/ha)

- 0 - 20
- 20 - 40
- 40 - 60
- 60 - 100
- 100 - 160
- 160 - 285

0 5 10   20 KM

Figure 46: **Predicted biomass in south Tamil Nadu (tropical forest)**

Legend (t/ha)

- 0.35 - 20
- 20.1 - 40
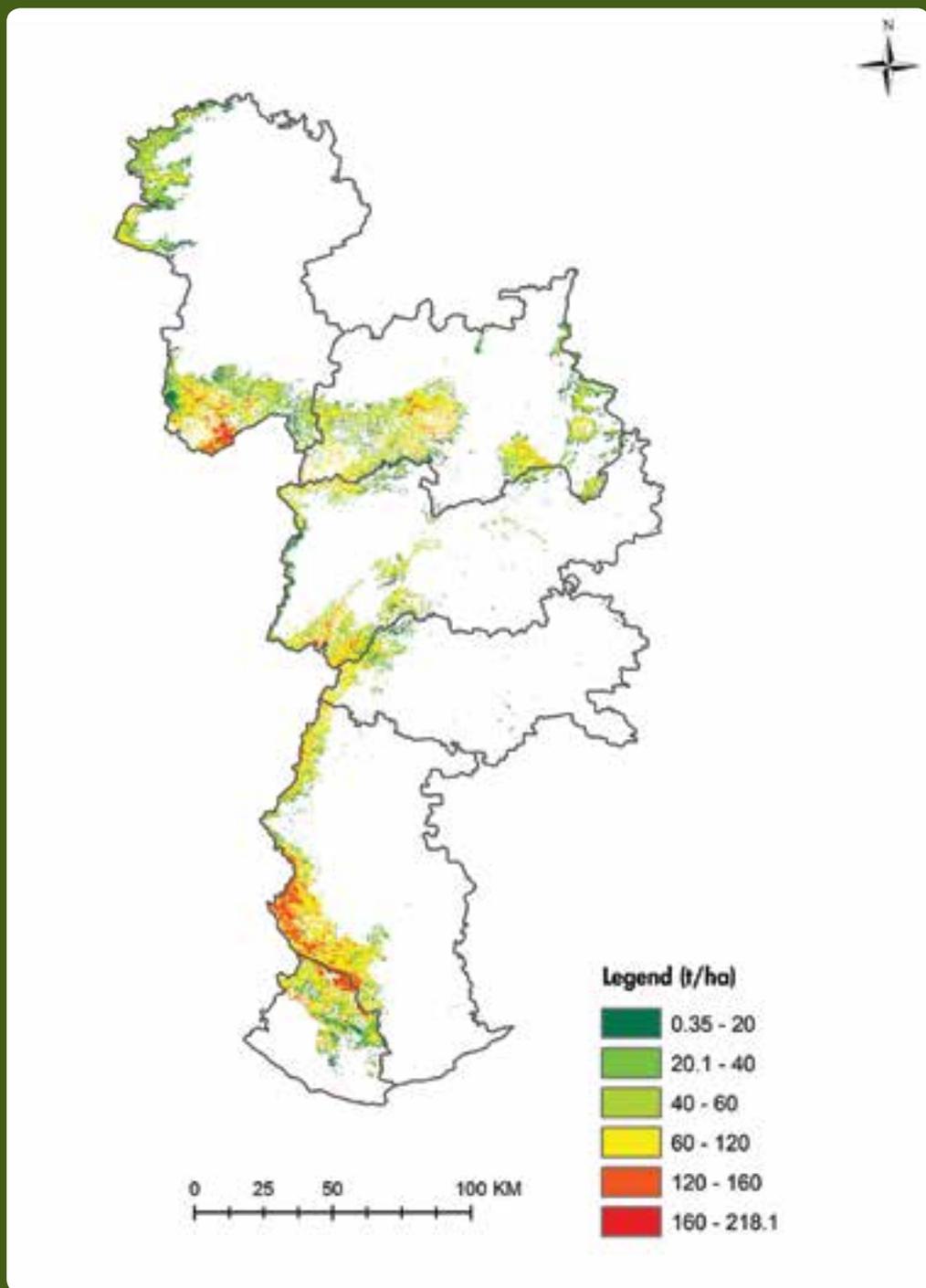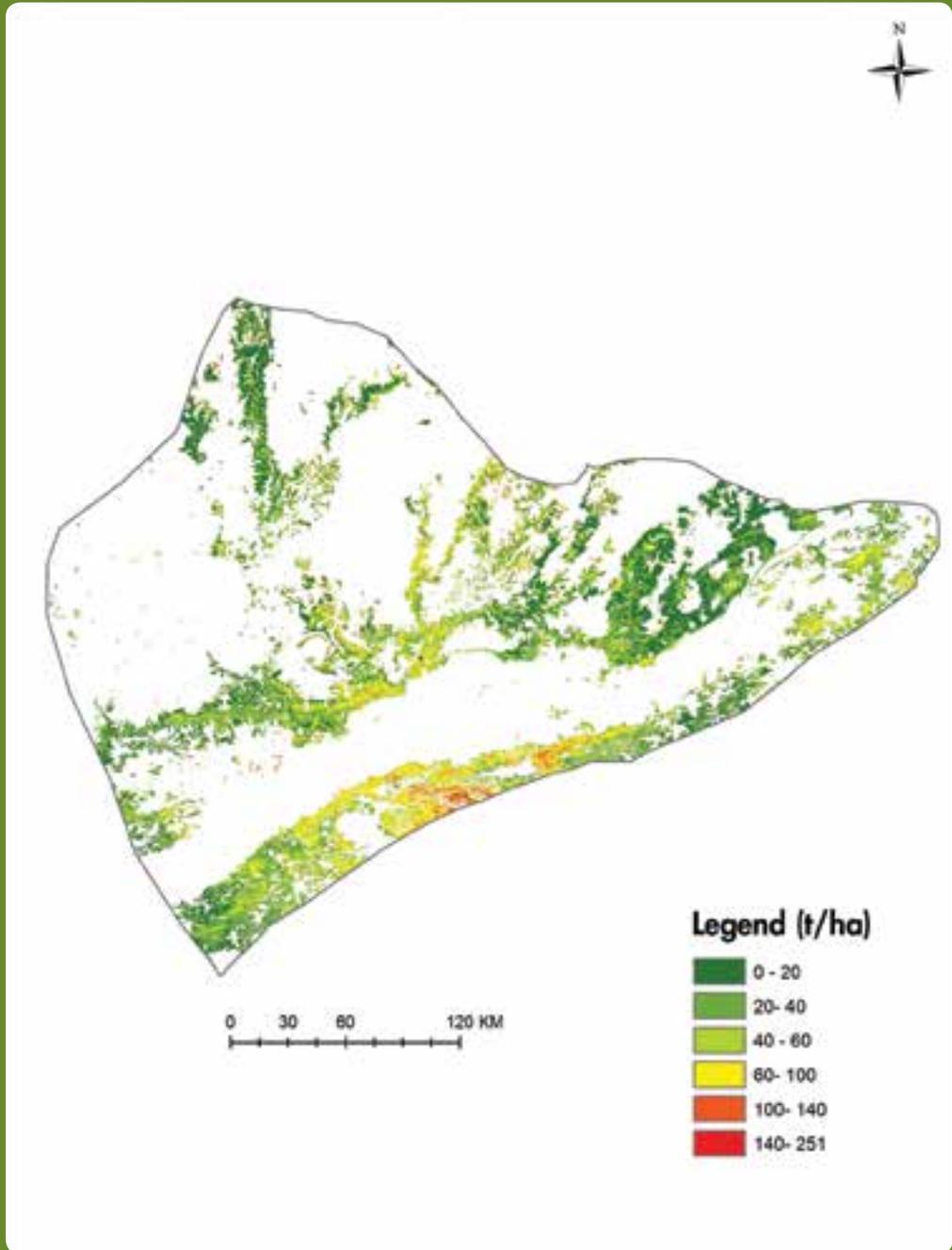- 40 - 60
- 60 - 120
- 120 - 160
- 160 - 218.1

0   25   50   100 KM

Figure 47: **Predicted biomass in part of Madhya Pradesh (deciduous forest)**

a carbon density for tropical dry deciduous forest ranging from 15.6 to 151 t ha^{-1}. FAO (2007) estimated the average biomass density in India as 70 t ha-1. Spatial estimates indicate differences in the range of observed and predicted AGB, which may be attributed to the distribution of field plots (field plots not covering all biomass ranges), phenological condition of the trees at the time of satellite data acquisition, selection of allometric equations, and wood density.

Uncertainty analysis

Measurement error related to tree variables, such as DBH, height, and weight

All trees with DBH greater than 10 cm were tagged and their diameter measured. The measurement is likely to have some imprecision, particularly in the case of irregularly shaped trunks. The standard errors associated with diameter and height are denoted as σ_D and σ_H. The error in diameter is expected to be an increasing function of D.

Species wood density (ρ) is used for each tree to convert species volume to biomass. There can be a corresponding error due to misidentification of tree species or variation within species (e.g. variation in wood density with age of tree).

Allometric models are usually in the form of

$$AGB = f(D,H,\rho)$$

The errors in diameter, height, and wood density are propagated to AGB through the allometric models.

$$\sigma_{AGB} = f(\sigma_D, \sigma_H, \sigma_\rho)$$

Chave et al. (2004) reported uncertainty in the AGB estimation of a single tree of diameter 10 cm or greater as 47% of the estimated AGB, 31% due to the allometric model and 16% due to the measurement uncertainty.

Uncertainty due to allometric model selection

The selection of allometric models is crucial in biomass estimation as different allometric models give different errors in the AGB estimation. We used three different sets of allometric models to assess the error associated with these models. For the first, we used a species specific volumetric equation for the dominant species in the study area; for the second, we used a state pooled equation for tree level biomass estimation; and for the third, we used a global volumetric equation (pan tropical equation) for biomass estimation. The biomass and standard errors were calculated at the site level (four plots per site).

Table 21: **Species specific allometric equations used in the study**

State	Species Name	Volume Equations
Madhya Pradesh	Madhuca longifolia	$V = -0.00092 - 0.55547D + 7.3446D^2$
	Lagerstroemia parviflora	$V = 0.01617 - 0.66446D + 9.71038D^2$
	Diospyros melanoxylon	$V = 0.0333 - 0.93267D + 8.15911D2 + 1.30093D^3$
	Acacia catechu	$V = 0.04235 - 0.7424D + 7.26875D^2$
	Tactona grandis	$V = 0.04346 + 8.79334D2 - 0.26352\sqrt{D}$
	Lannea coromandelica	$V = 0.046731 - 0.962906D + 7.301883D^2$
	Anogeissus latifolia	$V = 0.13053 - 1.94625D + 11.67213D^2$
	Shorea robusta	$\sqrt{V} = 0.30205 + 5.63243D - 2.2544\sqrt{D}$
	State Pooled Equation	$V = 0.0697 - 1.4597D + 11.79933D2 - 2.35397D^3$
Sikkim	Abies densa	$V = 0.12167 - 1.14D + 8.12D^2$
	Acer campbelli	$V = 0.06674 - 2.039D + 15.59D^2$
	Cryptomeria japonica	$V = -0.01097 + 5.30991D^2$
	Symplocos theifolia	$V = -0.03754 + 5.87D^2$
	State Pooled Equation	$V = 0.3555 - 3.7D + 12.59D^2$
Tamil Nadu	Adina cordifolia	$V = 0.296 - 2.829D + 12.207D^2$
	Anogeissus latifolia	$V = 0.289 - 2.653D + 11.771D^2$
	Artocarpus hirsutus	$V = 0.076 - 1.313D + 11.370D^2$
	Dillenia pentagyna	$V = 0.070 - 1.295D + 9.429D^2$
	Hopea parviflora	$V = 0.288 - 2.913D + 13.869D^2$
	Olea dioica	$V = -0.03001 + 5.75523D^2$
	Pterocarpus marsupium	$V = 0.70 - 1.295D + 9.429D^2$
	Tectona grandis	$V = 0.086 + 5.641D^2$
	Terminalia paniculata	$V = 0.13100 - 1.87132D + 9.47861D^2$
	Terminalia tomentosa	$V = 0.289 - 2.653D + 11.771D^2$
	State Pooled Equation	$V = 0.058 + 4.598D^2$

A total of 25 species specific allometric equations were used in the three study areas. The equations are listed in Table 21. The global and state pooled equations used for comparison are given in Equations 5, 6, 7, and 8.

Global equation used in the study:

$$B(D, \rho) = (\rho/0.6) \exp(-3.742 + 3.450\ln(D) - 0.148\ln(D)^2) \tag{5}$$

State pooled equation used for Sikkim:

$$Y = 0.3555 - 3.7D + 12.59D^2 \tag{6}$$

State pooled equation used for Madhya Pradesh:

$$Y = 0.0697 - 1.4597D + 11.79933D^2 - 2.35397D^3 \tag{7}$$

State pooled equation used for Tamil Nadu:

$$V = 0.058 + 4.598D^2 \tag{8}$$

The biomass range and standard errors for the different allometric models in the study areas are given in Table 22. The global volumetric equation has the largest standard error; the standard errors for the state pooled equation and species specific equations are comparable.

Table 22: **Biomass range and error associated with allometric models**

Forest type	Equation	Biomass range (t ha⁻¹)	Standard error range
Temperate forest	Species specific volume equation	13.50 – 425	2.20 – 177.1
	State miscellaneous equation	10.75 – 451	2.76 – 177.26
	Global equation	17.65 – 719	3.28 – 214.39
Deciduous forest	Species specific volume equation	5.89 – 104.82	0.93 – 22.48
	State miscellaneous equation	5.71 – 111.28	0.79 – 22.49
	Global equation	9.54 – 166.05	1.08 – 35.04
Tropical forest	Species specific volume equation	30.89 – 289.28	0.48 – 40.53
	State miscellaneous equation	30.56 – 278.59	0.45 – 49.66
	Global equation	41.25 – 566.71	3.79 – 88.26

The uncertainty for the different allometric models at the three study sites is shown in Figures 48, 49, and 50.

The results suggest that we should use the species specific volume equations to minimize the uncertainty in biomass estimation.

Sampling uncertainty

The sampling uncertainty is related to the size of plot to be inventoried and the number of trees in the plot. Errors in this category are mainly due to incorrect estimation of the plot area, trees missed or measured twice, or dead trees counted as alive.

Figure 48: **Uncertainty with different allometric models (Sikkim)**
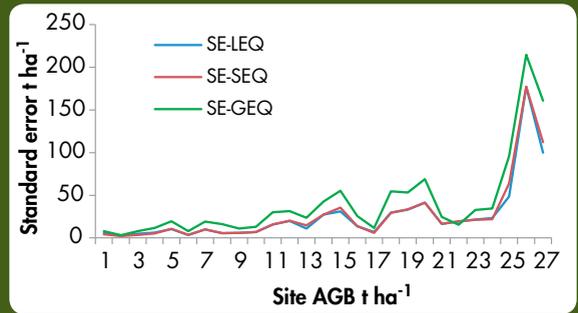
Figure 49: **Uncertainty with different allometric models (Madhya Pradesh)**
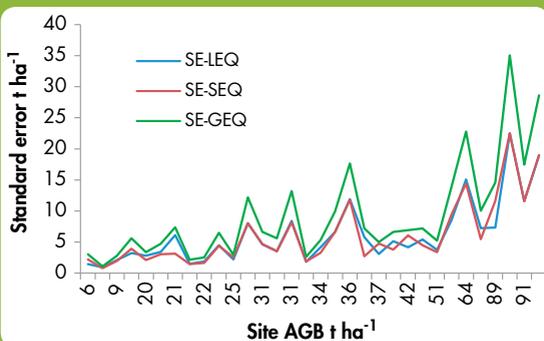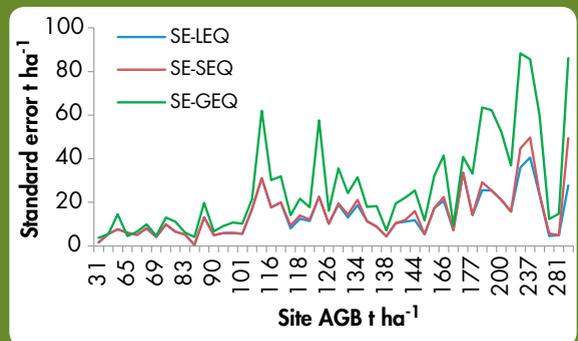

Figure 50: **Uncertainty with different allometric models (Tamil Nadu)**

The standard error in biomass estimation at the three study sites is shown in Figures 51, 52, and 53. The high standard error in plot biomass shows the variability in biomass at each site. The standard error increases with mean site biomass, and a small plot size gives a higher standard error since an occasional large tree will contribute a large fraction of the overall plot biomass. Tree level errors average out in large plots, and for this reason too it is advisable to establish large permanent plots

Representativeness of a network of small plots over a large forest area

Our study shows that the spectral models are area specific; a model developed for a particular region cannot be used in another region. Extrapolation of AGB estimates over a large area depends on topographic constraints and climatic conditions.

Figure 51: **Within site variation in biomass and standard error for temperate forest, (Sikkim, 28 sites)**
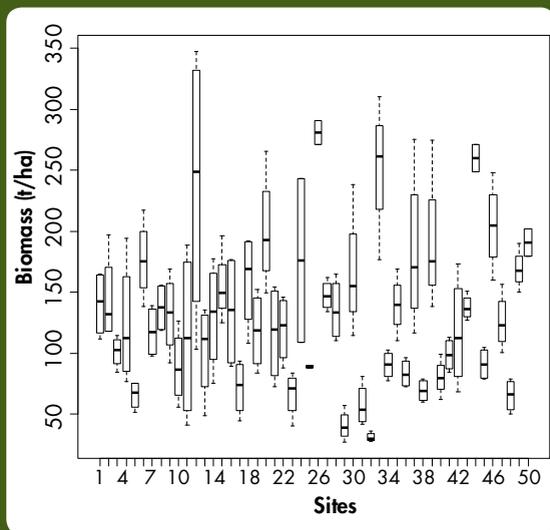
Figure 52: **Within site variation in biomass and standard error for deciduous forest (Madhya Pradesh, 32 sites)**
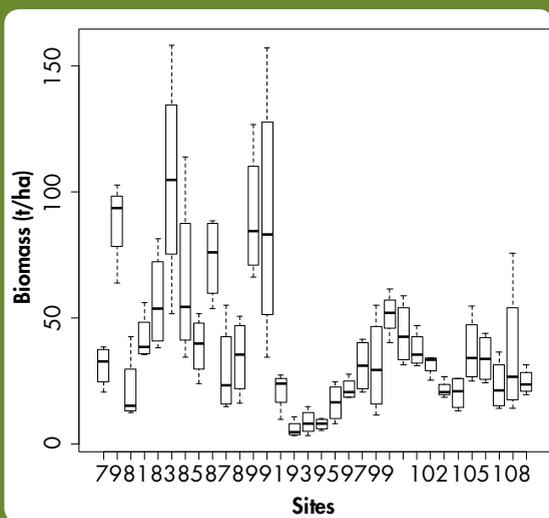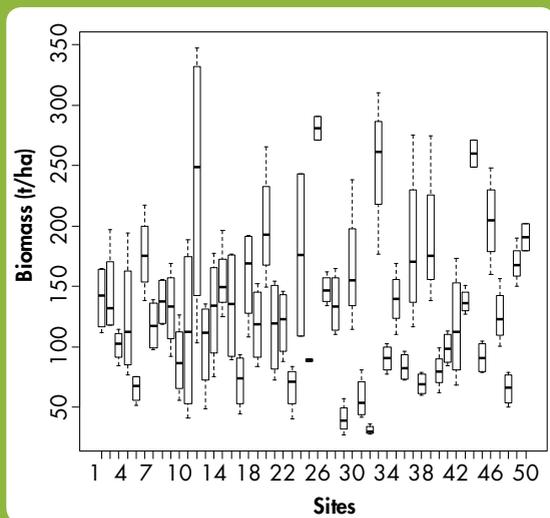

Figure 53: **Within site variation in biomass and standard error for tropical forest (Tamil Nadu, 50 sites)**

A single plot corresponds to a particular sample or small patch of forest and is unlikely to represent the variability in AGB on a large scale, thus AGB estimates for a large area should be assessed by establishing a network of randomly distributed plots over the whole forest area to assess the variability of forest types.

Table 23 shows the number of sample sites, AGB, and standard error at the three study areas. The standard error depends on the biomass range and number of sample sites, and is positively correlated with the ratio of AGB range and number of sample sites used.

Table 23: Sample sites, AGB, and standard error of spectral models

Study Area	Standard error (t ha^{-1})	Number of sites	Forest area (km^2)	AGB (t ha^{-1})	AGB/number of sites
Temperate	35.8	28	3,003	173	6.17
Deciduous	16.45	32	21,915	104	3.25
Tropical	3.27	50	4,831	146	2.92

It is advisable to distribute the sample plots in such a way that they cover all the biomass ranges in the study area; inclusion of available biomass estimates in the sampling design may improve the accuracy of AGB estimates.

Spatial uncertainty related to the geographic location of the sampling plot

The geographic latitude/longitude of the site measured with GPS is subject to some spatial error, and satellite images also have some spatial shift from the exact location. In addition, a sample site of 250 x 250 m doesn't fit perfectly on pixels. Thus the pixels used for the spectral models may not be the actual pixels, and the regression equations used for AGB estimation may have uncertainty errors due to this spatial shift. This is the spatial uncertainty.

The regression coefficient observed for the three study sites may not be the actual coefficient, it could be anywhere between the best and worst possible regression coefficient. The spectral models for each of the three sites were moved over four surrounding pixels to get the best and worst possible fit. The results are shown in Figures 54, 55, and 56. The worst and best fit gives the possible range of r^2 for the spectral model.

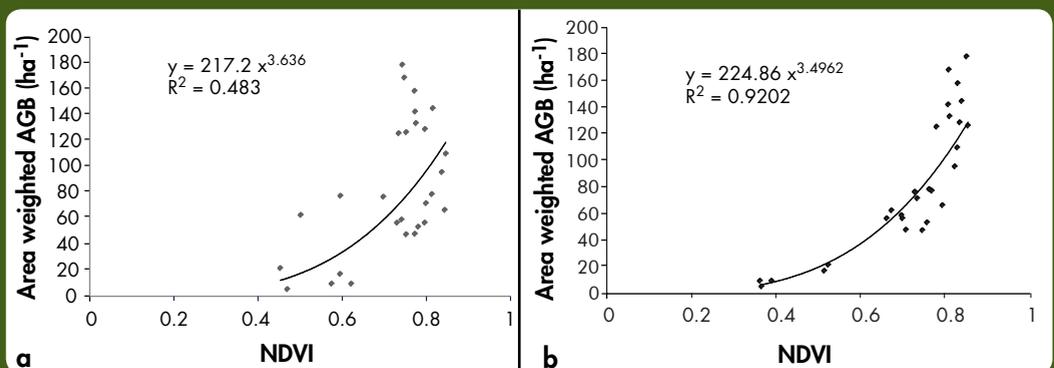**Figure 54: Worst (a) and best (b) possible fit for Sikkim**

a — $y = 217.2\,x^{3.636}$, $R^2 = 0.483$

b — $y = 224.86\,x^{3.4962}$, $R^2 = 0.9202$

Figure 55: **Worst (a) and best (b) possible fit for Madhya Pradesh**
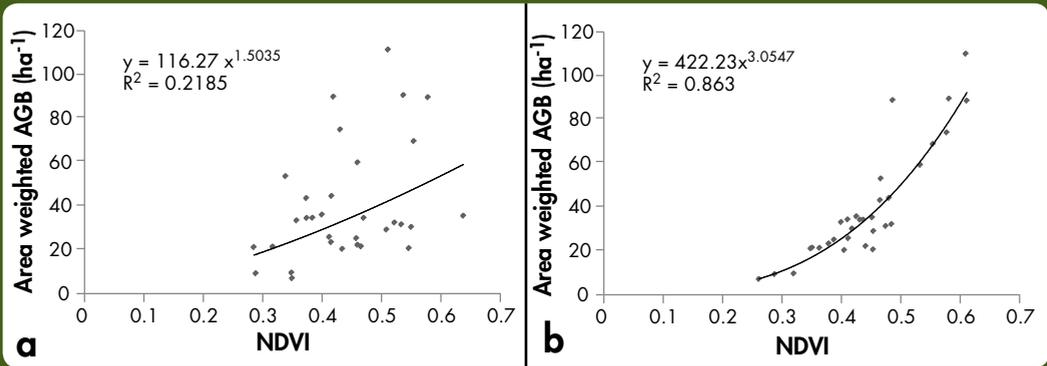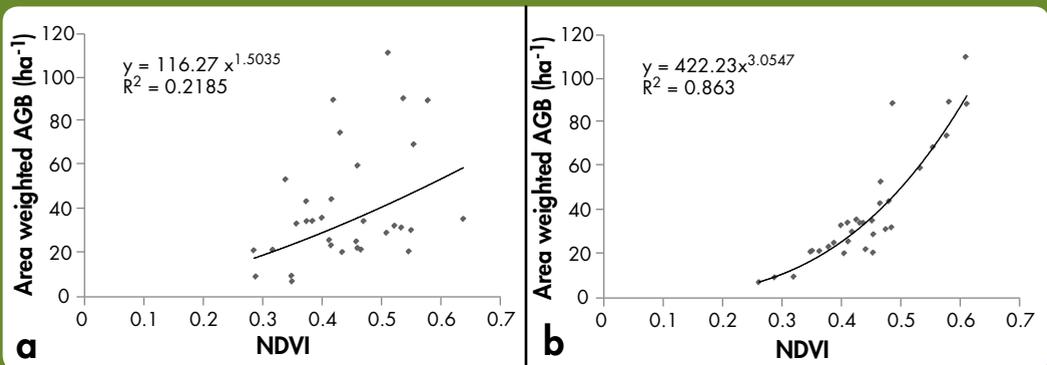

Figure 56: **Worst (a) and best (b) possible fit for Tamil Nadu**

Conclusion

Our results show that integration of remote sensing data with field inventory data is a useful approach to obtain improved forest AGB estimates. Three different study areas were selected to check the suitability of spectral models under different climatic conditions. The high r^2 values of 0.787, 0.721, and 0.735 indicate a significant relationship between AGB biomass and satellite-derived NDVI.

Field inventory is an efficient way of assessing biomass and carbon, but it has some associated uncertainties. The steps required to avoid these uncertainties are as follows:

- Allometric models are a basic requirement for AGB estimates using field inventories. Uncertainty in the AGB estimates depends largely on the selection of allometric model. It is advisable to use a species specific volume equation to minimize the uncertainty in biomass estimates.
- A small plot size gives a higher standard error as individual large trees contribute a large fraction of the overall plot biomass. Tree level errors average out in large plots, thus it is advisable to establish large permanent plots.
- Sample sites should be carefully distributed to ensure adequate coverage over different vegetation types and crown density. Inclusion of available AGB estimates in the sampling design may significantly improve the AGB estimates.

Acknowledgements

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Texture Analysis of Very High Spatial Resolution Optical Images as a Way to Monitor Vegetation and Forest Biomass in the Tropics

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*S*pace observation is acknowledged as quintessential for providing reliable baseline assessment and monitoring strategies for vegetation at multiple scales over extensive territories with a low population and limited accessibility. Optical satellite imagery represents the major source of data and covers an ample continuum of image resolution and swath. Yet vegetation monitoring in both the dry and wet tropics has long been hampered by insufficient pixel resolution that renders the well-mastered, pixel-wise classification techniques inefficient. The increasing availability of images with high spatial resolution (HSR, pixels of 10 m or less) to very high spatial resolution (VHSR, pixels of less than 1 m) has opened up new prospects by allowing the inference of vegetation properties from image texture features (i.e., local inter-pixel variability). In the present paper, we aim to illustrate this potential through recently published case studies dealing with semi-arid vegetation monitoring and baseline above ground biomass assessment in moist tropical forests. In both cases, we applied variants of the FOTO method (Fourier-based textural ordination) to quantify textural features in the images and relate them to meaningful vegetation properties, such as patterns of vegetation vs. bare ground in drylands, or crown and gap size distribution in forest canopy images. Textural ordination based on Fourier spectra provides a powerful and consistent framework for identifying prominent scales of landscape patterns and comparing scaling properties across landscapes. In the case of forest landscapes, texture features relate to crown size distribution and sometimes to inter-crown gaps and therefore are often good predictors of stand structure and biomass.

Keywords: above ground biomass, canopy grain, FOTO method, patterned semi-arid vegetation, tropical moist forest

Introduction

Reducing Emissions from Deforestation and Forest Degradation (REDD+) to combat climate change requires participating countries to periodically assess their vegetation and forest resources on a national scale. Such a process is particularly challenging in the tropics, where

territories are often large and poorly accessible, there are insufficient means for ground-based inventories, and it is difficult to visit field sampling sites frequently. The monitoring, reporting, and verification (MRV) process requires documenting spatiotemporal variations of vegetation and stand structure characteristics within the broad realm of 'forest land remaining forest land'. For this, providing meaningful information pertaining to vegetation biomass, cover, or functional properties is a challenge that demands smart synergies between remote sensing techniques and field data collection. However, although remote-sensing has long been seen as a useful source of data, progress has been slow over the last decades. Optical images are by far the most broadly available type of space-borne data, but their limited spatial resolution (i.e., large pixel size) has hindered applications in landscapes that do not show strong contrasts among vegetation and land-use types. This includes most dryland landscapes, as well as territories in the wet tropics that have not yet been cleared for commercial crops.

In the wet tropics, most of the vegetation types of interest have sufficient photosynthetic vegetation cover to be within the range of signal saturation of existing optical and radar sensors, making it difficult to discriminate and characterize different vegetation types on a pixel-wise basis (Foody 2003). In arid and semi-arid landscapes, the progressive transition between vegetation types and land-use units renders the majority of pixels heterogeneous (Couteron et al. 2001). In both cases, the processing schemes that have proven particularly successful for monitoring intensive crop encroachment and deforestation using high to moderate optical remote sensing images no longer suffice.

Very high spatial resolution (VHSR) imagery of approximately 1 m resolution, provided by satellites such as GeoEye, Ikonos, Orbview, Quickbird, or Pleiades, has now become widely available at an affordable cost, or even free in certain locations via Google Earth, or archives such as for Orbview. In the following, we show from recent studies that the increased availability of optical images of high to very high spatial resolution opens up new avenues for directly monitoring important vegetation properties such as above ground biomass and vegetation cover. These images can also provide indirect evidence of ecological processes that are shaping vegetation dynamics. Increased spatial resolution enables a move away from pixel-wise classification to schemes based on the analysis of textural properties of images at scales that are meaningful with respect to the vegetation properties under study.

In the specific case of forest territories, VHSR greatly increases the potential for texture analysis of canopy images by enabling texture information to directly reflect the contrast between sunlit and shadowed tree crowns, and thus provide information on the size distribution of crowns and inter-crown gaps (Couteron et al. 2005; Malhi and Roman-Cuesta 2008; Palace et al. 2008). Texture analysis of canopy satellite images can therefore furnish an objective, semi-automatic visual interpretation of the aerial photographs that have been used in forestry since the 1950s, but barely translated into processing as digital images. In fact, foresters and ecologists have long known that canopy aspect in 2D views provides useful information on forest structure. Texture analysis can also be applied to historical series containing digitized aerial photographs and satellite images.

To illustrate how HSR and VHSR optical imagery and texture analysis (specifically the FOTO method) may foster the use of space observations for vegetation monitoring, we review broad scale studies carried out by our group in dry and wet tropical environments. In the tropical case, the reviewed studies addressed the timely question of documenting stand above ground biomass (AGB) using space observation. In the dryland studies, we have focused on vegetation types featuring patterns of bare soil vs. dense (generally woody) vegetation that display periodic spatial patterns. Such striking patterns are a worldwide feature at the interface between deserts and savannas (Deblauwe et al. 2008) and have inspired numerous mechanistic models (e.g., Lefever et al. 2009). The patterns display four main morphologies: bands (so-called 'tiger bush'), gaps of bare soil within vegetation, labyrinths, and spots of vegetation against a bare soil background. All published models for explaining such patterns embody a common principle of self-organization and make concordant predictions on how environmental factors may modulate these morphological properties. This array of predictions needs to be corroborated using synchronic and diachronic large-scale observations, thus HSR imagery and texture analysis were used. Both forest and dryland studies exemplified the relevance of HSR and VHSR imagery for monitoring vegetation and associated carbon stocks.

Methodology

The gray-scale values in panchromatic digital images convey different meanings depending on the ecological context and the overall contrasts of vegetation. In semi-arid landscapes, bright pixels usually correspond to bare soil, intermediate gray-scale levels to grass cover, and darker pixels to woody vegetation. As a first approximation, gray-scale levels can thus be considered as a monotonically decreasing function of AGB. In forested landscape images the interpretation is different since the fully sunlit crowns of canopy trees appear in white/light gray, while the shadowed inter-crown gaps are dark-grey or black. A monotonic relationship between gray-level scale and canopy height can thus be assumed in the absence of substantial relief-induced shadowing. In both cases, signal variation among neighbouring pixels, i.e., texture, is relevant for providing indirect information on vegetation.

Implementing the FOTO (Fourier Textural Ordination) method (Couteron 2002; Proisy et al. 2007) means first subdividing images into windows of a size consistent with the targeted vegetation properties. To analyse forest canopies, a square window of about 1 ha is generally relevant and is consistent with a popular field plot size. In semi-arid landscapes, previous studies have used window sizes in the range of 160 to 450 m depending on the scale of the bare soil vs. vegetation patterns that are of interest. Systematic analysis has shown that the results, i.e., the main textural gradients obtained, are to some extent robust against variation in window size (Couteron et al. 2006). When applying FOTO, each of the windows originating from one or several digital images is submitted to a two-dimensional Fourier transform and computation of a two-dimensional periodogram. The aim is to extract a simplified textural characterization (in terms of coarseness) via the computation of a 'radial' or r-spectrum. This means summing the periodogram values within ring-shaped concentric bins of unit width (same wave number) and neglecting information related to orientation and

possible anisotropy. Spectra computed from many image windows of the same size are systematically compared using principal component analysis (PCA), which provides an ordination along a limited number of coarseness vs. fineness gradients. In so doing, windows are treated as statistical observations that are characterized and compared on the basis of their spectral profile, i.e., the way in which window gray-scale variance is broken down in relation to Fourier harmonic spatial frequencies. For all the reviewed case studies, we applied the FOTO method in line with the procedure presented in Proisy et al. (2007) and using routines developed in the MatLab environment.

As an illustration, Figure 57 shows the Fourier signatures (r-spectra) for dryland vegetation image windows. The variants of the FOTO method automatically rank windows along coarseness gradients in a way that is consistent with the visual interpretation (see Couteron et al. 2005 and Ploton et al. 2012 for forest canopies, and Couteron et al. 2006 for dryland). Figure 58 provides an example of FOTO ordination using VHSR images of lowland forests in a logging concession in central Africa as an example of the analogy with human photo-interpretation, and the ability of the method to implement photo-interpretation in a consistent and objective way (i.e., via quantitative indices) over a large area. In addition to the FOTO ordination based on the isotropic r-spectra, it is in some cases useful to extract from the periodogram information on possible dominant orientations in the image windows. This has proven specifically useful for studies dealing with semi-arid patterned vegetation because it is

Figure 57: **Examples of the main morphologies of spatially periodic semiarid patterns from optical HSR images (top panel) and associated Fourier r-spectra (bottom) as observed in the Sudan study area in Deblauwe et al. (2011).** In the bottom row, abscissa are spatial frequencies (cycles km^{-1}) while ordinates feature rescaled r-spectra. Note the shift of the mode from left to right that contributes to the automatic discrimination and mapping of the morphologies (the dominant wavelength systematically decreases from spots to labyrinths and to gaps).
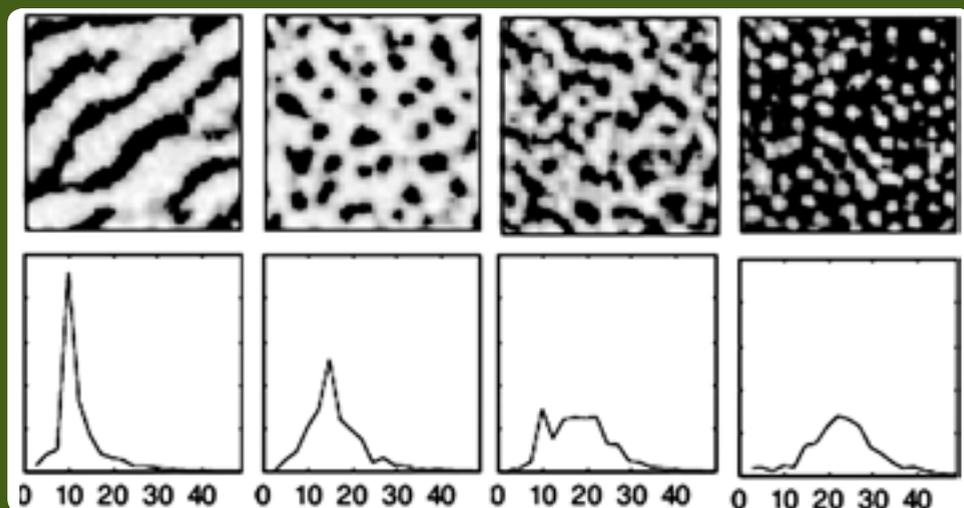
Figure 58: **FOTO textural ordination results from a VHRS panchromatic canopy image (GeoEye) over a logging concession in the lowland forests of southern Cameroon.** The analysis yielded two main texture gradients (PCA axes) which are illustrated from specific image windows of 1 ha. The horizontal gradient opposed images marked by large tree crowns and sometimes felling gaps (or logging tracks) to images made of many small-sized crowns (in unlogged, seasonally flooded valleys). The vertical gradient pointed to canopies dominated by medium-sized crowns
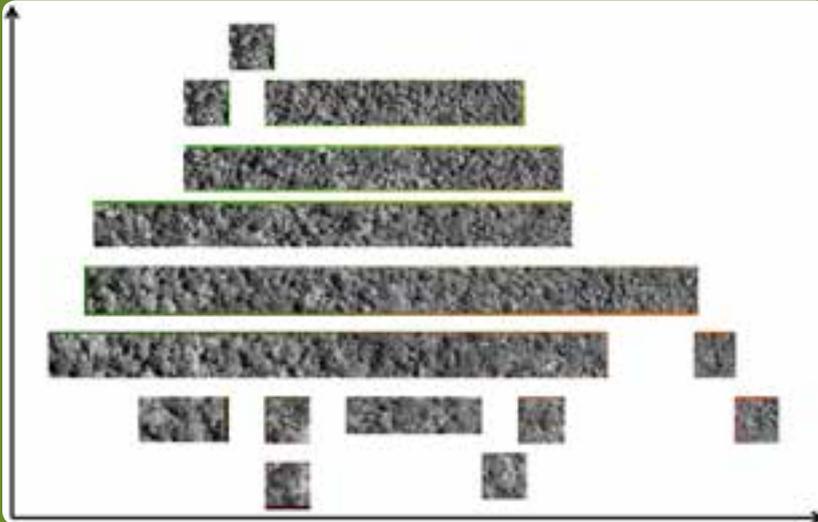
of relevance in discriminating and mapping the main morphologies (e.g., labyrinths vs. gaps, see Figure 57) in a semi-automatic way (as in Deblauwe et al. 2011). Following Couteron and Lejeune (2001), this is done by averaging periodogram values for successive angular sectors. For the case study in central Sudan (semi-arid patterned vegetation; Deblauwe et al. 2011) HSR panchromatic images (10 m resolution) were used. Window size was set to 410 m^2 and 132,388 such windows were used in the study. For the forest studies, Geoeye and Ikonos images and window sizes of 100 to 125 m were used. Ploton et al. (2012) treated 1,253 windows of 125 m over the evergreen forest of the Western Ghats of India.

Results

Studies of semi-arid vegetation

Studies carried out in several countries in the sub-Saharan African Sahel (northern Burkina Faso, southern Niger, and central Khordofan in Sudan) showed that the FOTO method applied to HSR panchromatic images allowed identification of spatially patterned vegetation against non-patterned savanna vegetation (characterized by no apparent bare ground). It also proved able to distinguish the four main morphologies of spatial patterns. In the Sudan study, classification and mapping of vegetation into four periodic pattern classes (Figure 57), and one non-periodic class enabled us to show a succession of patterns in the order predicted by self-organization models, namely non-periodic, gapped, labyrinth, and spotted, in a way that

paralleled decreasing mean annual rainfall. In addition, during the persistent drought that struck the Sahel through the 1970s and 1980s, we showed that transitions occurred diachronically along the same sequence: for example, in central Khordofan, labyrinths and gaps replaced non-patterned vegetation, while existing labyrinths and gaps ceded to spotted vegetation. All these changes meant an increase in the bare ground vs. vegetation ratio and concomitant decrease in AGB. In Niger, Barbier et al. (2006) witnessed a similar drought-concomitant extension of gapped patterns in place of continuous vegetation in a protected area. Non-patterned vegetation directly shifted to labyrinths in unprotected adjacent areas where the biomass intake through grazing and wood-cutting reinforced the effect of drought.

Above-ground biomass predictions from VHSR canopy images

Case studies corresponding to particular forested landscapes, typically of some hundreds of square kilometres, have shown that image PCA scores (FOTO textural gradients) generally display a good correlation with the stand quadratic mean diameter at breast height (DBH), and can thus be good predictors of AGB as measured in reference 1 ha field plots. Published results encompass mangrove forests in French Guiana (Proisy et al. 2007 from Ikonos images), tropical terra firme forests in French Guiana (Couteron et al. 2005 from digitized air photos), and forests in the western Ghats of India (Ploton et al. 2012 from Google Earth Ikonos images). Singh et al. (2014) successfully applied FOTO to AGB mapping in logging-impacted landscapes in Sabah, Malaysian Borneo. One of the clear advantages of FOTO (and more generally of texture methods) over pixel-wise processing of either optical or radar data of high to moderate spatial resolution (pixels of 10 to 300 m) is that texture indices from VHSR images appear immune to signal saturation effects up to AGB values of at least 500 Mg DM ha^{-1} (and probably more). AGB predictions with root mean square errors of less than 15–20% were achieved in the case of evergreen closed canopy forests in the case studies. Bastin et al. (2014) found similar errors in central Africa in spite of the forest types being more diverse (including semi-deciduous and open canopy forests). In all these studies, high resolution AGB maps (100–125 m pixels) were produced over regions of up to 400 km^2. The efficiency of the method can be explained by the allometric relationship that exists between crown diameters, which are reflected in the canopy texture analysis, and the bole dimensions (notably the DBH) that are classical predictors of total tree biomass. Antin et al. (2013) concluded that the DBH-crown relationship displays less inter-species variation than the tree-height allometry. A second important point that explains the relevance of canopy grain for predicting AGB is that 'large trees', whose crowns are always visible in the canopy, are known to contain most of the AGB.

Field plots are an invaluable reference for calibrating and testing any space observation method targeting AGB. But they are costly to acquire and therefore often too scarce to allow for systematic analysis of the reliability of the inversion process (canopy texture to AGB) in relation to the diversity of forest stand structures and acquisition conditions of the satellite images (i.e., sun height, sensor-sun angles, and others). It is well known and fairly intuitive that variation in acquisition conditions is liable to induce strong artificial variation in the

texture: the same portion of canopy will automatically display finer textures in configurations in which shadows are concealed from the observer. To multiply scarce field data and gain knowledge from virtual canopy images corresponding to known stand structures, we have proposed a modelling framework that allows simulation of forest canopy images for any type of forest with basic forest inventory data as the only input. This framework combines a simple 3D forest model named 'Allostand', using field-measured DBH distributions and allometry rules, with a radiative transfer model 'Dart' (Gastellu-Etchegorry 2008). The simulated images obtained appear to have good realism for textural analysis, and allowed us to verify that the FOTO indices correlate strongly with the median crown diameter of the virtual canopy scenes (Barbier et al. 2012). Simulated images also allowed validation of a simple method (called partitioned standardization) for attenuating the effects of discrepancies in acquisition conditions. However, systematically applying this principle at operational scale would require a very large array of VHSR images grasping both the breadth of the regional stand structure gradients and very diverse sun-view configurations. Such an array is not yet available, but assembling it could be an objective for donors keen to back the development of MRV methods for the REDD+ mechanism.

Conclusion

Texture analysis of HSR and VHSR optical images is able to provide meaningful information on vegetation properties and biomass that could be crucial in many regions and countries for reaching operational and cost-efficient MRV schemes. Results from such analyses can also benefit basic ecology and vegetation science. In the case of semi-arid patterned vegetation, we demonstrated that the corresponding landscapes are reactive to decadal climate variations and are sentinels for climate change. VHSR imagery is increasingly available, and versions of Ikonos images downloadable from Google Earth (Ploton et al. 2012) proved suitable for the analyses reviewed in this paper.

Acknowledgements

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Estimating Above Ground Biomass of Tropical Mixed Deciduous Forests Using Landsat ETM+ Imagery for Two Reserved Forests in Bago Yoma Region, Myanmar

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*R*educing carbon emissions from deforestation and degradation is of central importance in efforts to combat climate change, and many countries are emphasizing quantification of the carbon emissions from deforestation and forest degradation. This paper focuses on a study under the 'Mitigation of climate change impacts through restoration of degraded forests and REDD Plus activities in Bago Yoma Region, Myanmar' project implemented under the auspices of Korea Forest Services (KFS). The study focused on estimation of above ground biomass (AGB) using Landsat ETM+ for two reserved forests in the Bago Yoma region, Myanmar. It demonstrates the use of spatially explicit AGB estimation over a large area using forest inventory data and satellite imagery and providing basic information on biomass/carbon for the monitoring, reporting and verification (MRV) system. Although the special reflectance of the Landsat image is not sufficient on its own to provide good results for estimating forest density in tropical mixed deciduous vegetation, in this study it provided relatively good results for estimating AGB.

Keywords: REDD, AGB, Landsat, Lidar, MRV, NDVI, MLR, two-dimensional approaches, three-dimensional approaches

Introduction

An estimated 16.9 million hectares of tropical forest are thought to be lost annually, mainly through conversion for agriculture, and more than 5 million hectares become secondary forests following timber harvesting. Thus Reducing Carbon Emissions from Deforestation and Forest Degradation (REDD+) in developing countries is of central importance in efforts to combat climate change. Many developing countries are emphasizing the quantification of carbon emissions from deforestation and forest degradation; which means obtaining information on forest clearance and carbon storage. Many studies have looked at estimating the carbon and biomass status of forest areas using a variety of methods in order to understand the carbon storage capacity of forests.

In general, forest biomass includes above ground and below ground living mass, including trees, shrubs, vines, roots, and the dead mass of fine and coarse litter associated with the soil. Due to the difficulty of collecting field data on below ground biomass, most research on biomass estimation has focused on above ground biomass (AGB).

Many approaches and data sources have been used for estimating AGB, including field measurements, GIS, and remote sensing. Traditional techniques based on field measurements are generally considered to be the most accurate way of collecting biomass data. A sufficient number of field measurements are a prerequisite for developing AGB estimation models and for evaluating the AGB estimation results. However, these approaches are often time consuming, labour intensive, and difficult to implement, especially in remote areas, and they cannot provide information about the spatial distribution of biomass over large areas. GIS-based methods using ancillary data are also difficult because of problems in obtaining good quality ancillary data, indirect relationships between AGB and ancillary data, and the comprehensive impacts of environmental conditions on AGB accumulation, and these approaches have not been applied extensively for AGB estimation. In recent years, remotely-sensed data have become the primary source for biomass estimation and remote sensing techniques have become prevalent in estimating AGB (Lu 2006).

The advantages of remotely-sensed data lie in the repetitive nature of data collection, a digital format that allows fast processing of large quantities of data, the high correlation between spectral bands and vegetation parameters, and the broad spatial coverage. Remote sensing has become the primary source for large area AGB estimation, especially in areas with difficult access, and remote sensing-based AGB estimation has increasingly attracted scientific interest. AGB can be directly estimated from remotely-sensed data using different approaches including multiple regression analysis, K nearest-neighbour, and neural network, and indirectly estimated from canopy parameters, such as crown diameter, which are first derived from remotely-sensed data using multiple regression analysis (frequently used) or different canopy reflectance models.

Landsat ETM+ data is the most widely used source of remotely-sensed imagery for forest biomass estimation. Many studies have used geo-statistical approaches to generate spatially explicit maps of AGB from field plots and to improve upon existing biomass estimation. Many methods for biomass estimation rely on the link between ground plots and satellite imagery, and GIS is often used as a mechanism for integrating multiple data sources such as forest inventory and remotely sensed data.

Estimation of forest AGB is required as an input for the national forest monitoring, reporting, and verification (MRV) system required under the 1997 Kyoto Protocol. National-level forest biomass estimation is necessary and might be an important attribute. However, in Myanmar information related to AGB is still very limited and thematic maps of AGB are still lacking. This study focused on a preliminary study for AGB estimation using Landsat ETM+ for two reserved forests in Bago Yoma with the support of Korea Forest Services under REDD+ initiative

activities. The objective was to demonstrate spatially explicit AGB estimation over a large area using a combination of forest inventory data and satellite imagery, and to provide basic information on biomass/carbon for the MRV system.

Methodology

Study area

The study area consisted of two contiguous reserved forests, Sa Byin and Lon Yon, in the Central Bago Mountains in Myanmar (Figure 59). The total area was approximately 10,300 ha, with an elevation range from 70 to 523 masl. The average annual rainfall during the period 1995–2006 at the nearest meteorological stations was 1,917 mm. The forest type is predominantly mixed deciduous, which is by far the most economically important forest type in Myanmar. The area is an important timber production area and the study area spans a wide range of forest structure, as reflected in various forest parameters, which together with the large number of tree species results in heterogeneous forest cover.

Data sources

Landsat 7 Enhanced Thematic Mapper plus (ETM+) imagery was selected for AGB estimation due to its suitability in terms of resolution (the spatial resolution of 30 m x 30 m is adequate to

Figure 59: **Location of the study area**
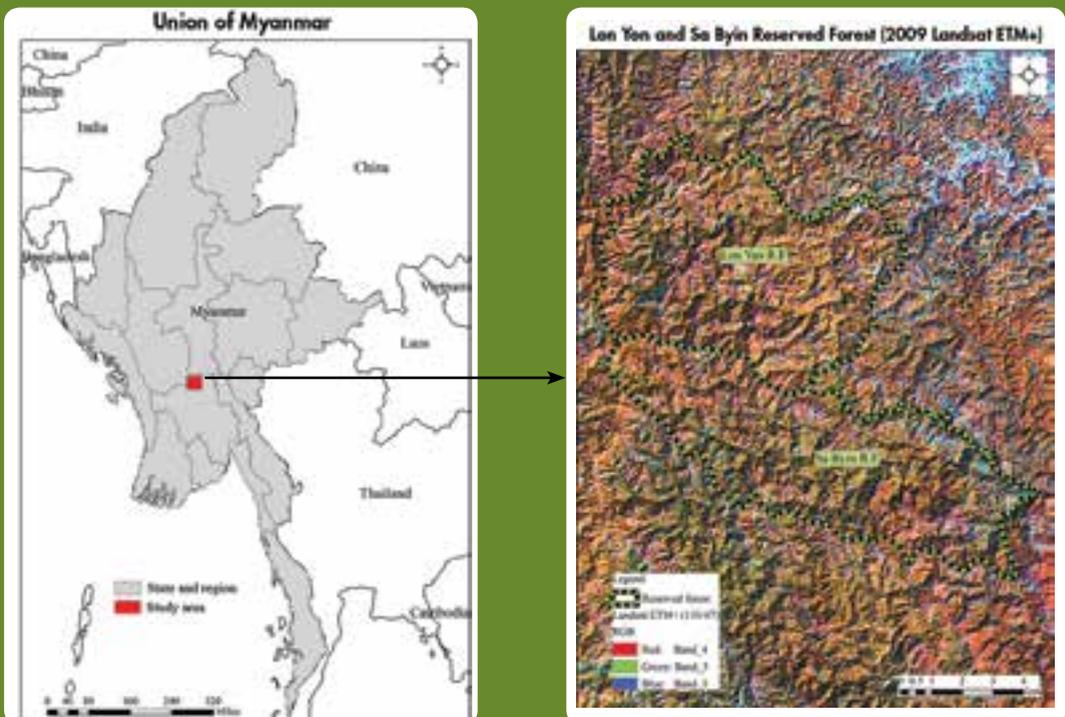
assess information at the forest stand level) and practical considerations associated with its use. The image for 23 January 2009 (path/row: 133/47), a gap-filled SLC-off product, was downloaded from the Global Land Cover Facility. The image was georeferenced to the coordinate system of the study area (WGS 84, UTM projection, Zone 46N) and then converted from digital number values to reflectance according to Jakubauskas and Price (2000) and Joshi et al. (2006). The NDVI for the study area was then calculated to support the field survey.

Ground data were collected during March 2012. We used sample plots of 40 m × 40 m in order to match the spatial resolution of the satellite image. The total number of sample pots was 220. As the study area is a production forest, it could be assumed that the time difference between image acquisition date and survey time would not have had any marked impact on the study.

Sampling design

As the total area was around 10,300 ha, complete enumeration was impossible within the available time frame. A stratified random sampling design was used.

Representative samples were selected based on the vegetation density calculated from the NDVI. The NDVI was calculated using the spectral reflectance of the near infrared and red channels in the satellite image using $NDVI = \frac{(NIR - RED)}{(NIR + RED)}$. The NDVI values range from -1 to +1; we divided the values into five classes as shown in Table 24 (total area) and Figure 60 (spatial distribution).

For plot selection, a systematic 200 m grid-intersect of sample plots was prepared for the study area using Hawth's analysis tools for ArcGIS, a total of 2,600 sample plots. The vegetation density was extracted for each plot using the Arcgis spatial analysis tool. Then a specific number of plots were selected at random within each of the five vegetation density classes as shown in Table 25 and a 40 m x 40 m sample plot delineated for each selected plot, giving a total representative sampling percentage by area of 0.34%. The locations (coordinates) of sample plots were recorded in GPS for field data collection (Figure 61).

Table 24: **Area of vegetation density classes based on NDVI**

NDVI	Vegetation density class	Area (ha)
<0	Class 1	3.33
>0 to <0.1	Class 2	178.74
>0.1 to <0.2	Class 3	2,988.18
>0.2 to <0.3	Class 4	6,542.46
>0.3	Class 5	555.21
Total area		**10,267.92**

Figure 60: **Vegetation density in the study area based on NDVI (in 2009)**

Legend:
- Reserved forest
- <0
- 0 to 0.1
- 0.1 to 0.2
- 0.2 to 0.3
- >0.3

0 0.5 1 2 3 4 km
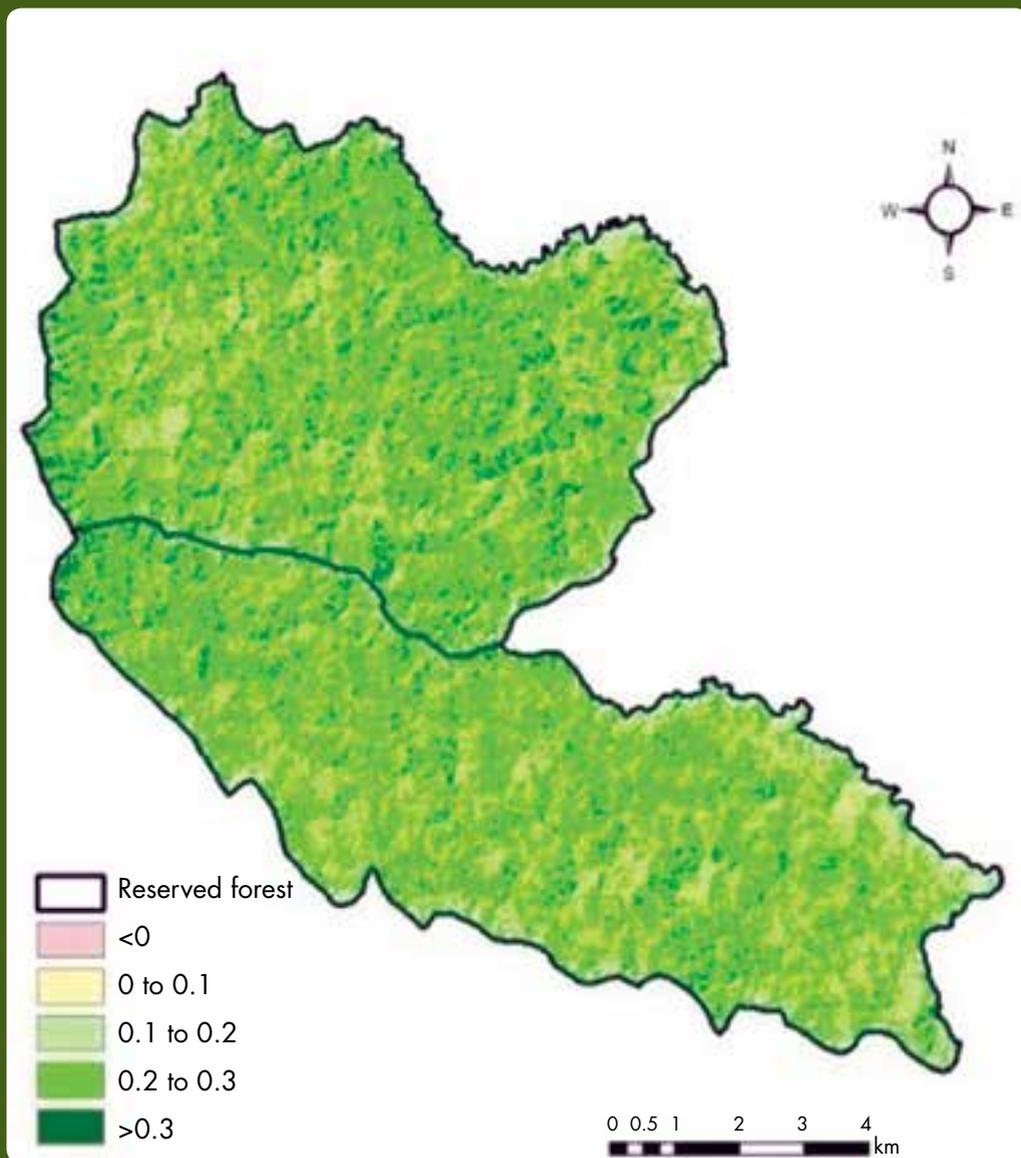
Inventory in sample plots

The sample plot design is shown in Figure 62. Subplots of 20 m x 20 m and 10 m x 10 m were delineated within the 40 m x 40 m sample plot. We recorded trees with a DBH of > 20 cm inside the 40 m x 40 m plot (plot A), trees with a DBH of > 10 cm (saplings) inside the 20 m x 20 m

Table 25: **Number of selected samples**

| NDVI class	Stratified plots	Selected plots
Class 1	37	20
Class 2	56	50
Class 3	755	50
Class 4	1,616	50
Class 5	136	50
Total	**2,600**	**220**

Figure 61: **Location of sample plots within the study area**
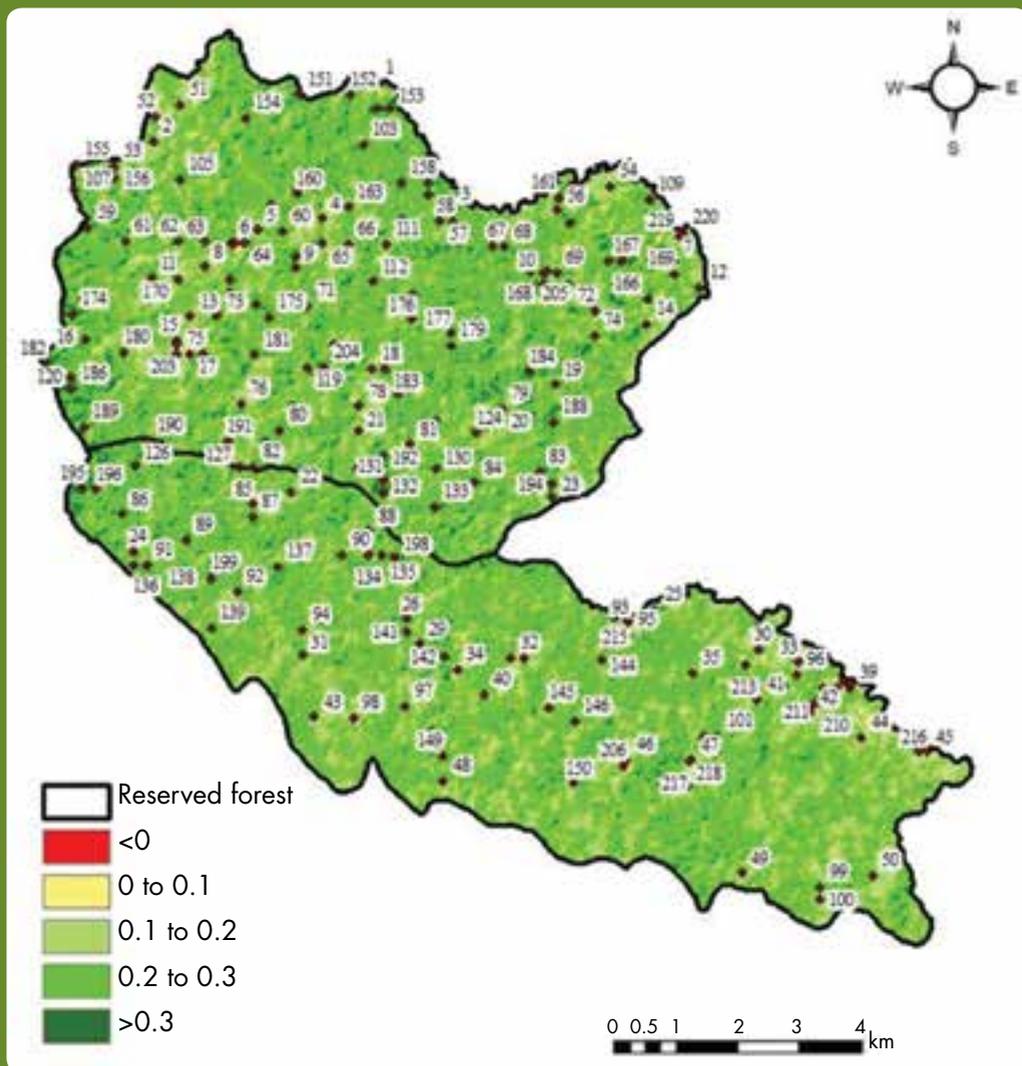
subplot (plot B), and trees with a DBH of > 5 cm (seedlings) inside the 10 m x 10 m subplot (plot C). The location of the sample plots was checked at the centre using GPS and their respective coordinates.

The field inventory (ground truth) was carried out by the Inventory Section of the Planning and Statistics Division of the Forest Department. The inventory crew recorded data with field sheets and followed the instructions developed under the National Forest Inventory, Myanmar. Unfortunately, the field plots did not contain enough information for non-forest classes, for this we set up sample plots subjectively using visualization of the images.

Figure 62: **Field survey sample plot design**
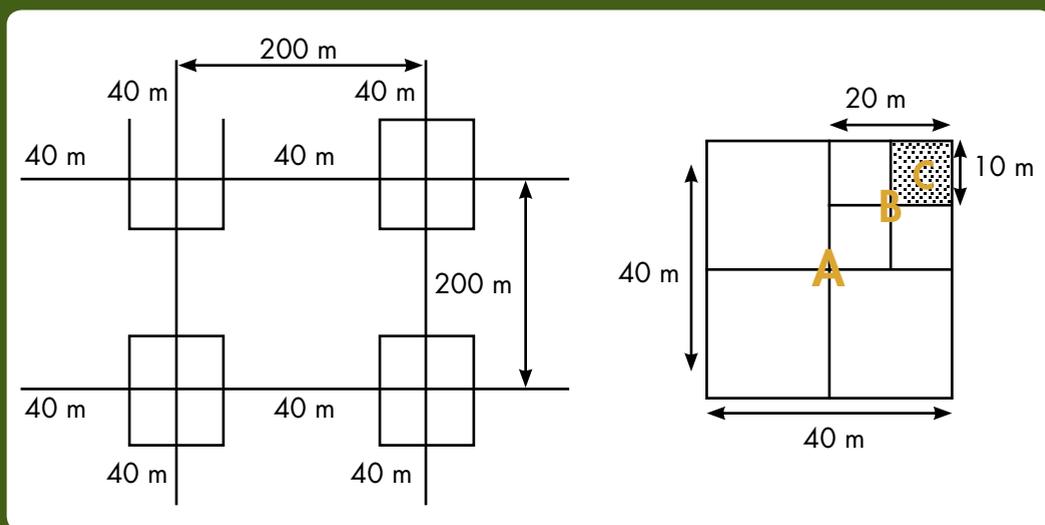
Estimation of AGB for field sample plots

We defined forest biomass density as the total AGB per unit area (1,600 m²) of trees with a DBH of 5 cm or more. The inventory data from each sample plot was first put into Microsoft Excel and the biomass of each tree estimated using a biomass regression equation and field-measured DBH (Brown et al. 1989). After generating the tree level biomass, the AGB for each sample plot was summed and converted into stand level total AGB (tonnes (t)/plot and t/ha). The biomass regression equation used was developed for tropical trees of DBH 5 to 148 cm using 170 trees and was as follows:

$$Y = 42.69 - 12.80 (D) + 1.242 (D^2)$$

where Y = biomass per tree in kg and D = DBH in cm; adjusted r^2 was 0.84.
Selection of training samples for multiple linear regression was done using PASW 18. The 220 samples were divided into 112 training samples and 108 samples for accuracy check of the output thematic map. The descriptive statistics of sample plots used for training and accuracy are shown in Table 26.

Table 26: **Descriptive statistics of sample data used for training and accuracy (biomass t/ha)**

Category	Minimum (t/ha)	Mean (t/ha)	Maximum (t/ha)	Standard deviation
Training (112 plots)	0	136.66	423.79	9.35
Accuracy (108 plots)	0	142.51	510.87	11.85

Generation of regression model for remote sensing biomass estimation

Multiple linear regression (MLR) is a general statistical technique used to analyse the relationship between a dependent variable and several independent variables or covariates (Hair et al. 2006). MLR has been used to estimate forest parameters such as forest age and forest canopy density using spectral responses of remotely sensed data (Ripple 1994; Salvador and Pons 1998; Jakubauskas and Price 2000; Joshi et al. 2006; Mon et al. 2012a,b). In the present study, biomass was estimated using the spectral reflectance of six Landsat ETM+ bands (bands 1–5, 7). The spectral reflectance values of the six bands were extracted for the 112 training samples. Statistical analysis was conducted in PASW 18. The linear relationship between the dependent and independent variables was examined in scatter plots. The results did not show any non-linear relationships between the dependent and independent variables. MLR was then run to estimate the regression model.

High collinearity between the independent variables poses a statistical problem, thus we first examined collinearity between the independent variables using the variance inflation factor (VIF) and tolerance in the regression. High collinearity between independent variables occurs when tolerance < 0.20 or VIF > 4 (Allison 2001, cited by Eeckhaut et al. 2006). We subsequently excluded four variables, the spectral reflectance values of landsat ETM+ bands 1–3 and 7, from the independent variables because of the high correlation among them. Normality, linearity, homoscedasticity, and independence of the error terms were examined to verify whether the regression model was applicable for estimation (Hair et al. 2006). Normality of the equation was checked using the histogram of residuals. Linearity of the overall equation was examined through the residual plots. Homoscedasticity was examined by plotting the Studentized residuals against the predicted dependent values. Independence of the error terms was identified by plotting against sequencing variables. All the diagnoses exhibited linear patterns and indicated that application of the regression model was acceptable. The equation used in the MLR model for estimating biomass was

$Y = 0.963 + 0.359 \, B4 - 0.248 \, B5$
$(R^2 = 0.64, F109 = 36.978, P \leq 0.01)$

where Y is the predicted biomass and the variables $B4$ and $B5$ are the spectral reflectance values of the ETM+ bands 4 and 5. A thematic biomass map was generated in ArcGIS 9.3 using the above equation.

Results

Accuracy assessment

Evaluation of the model performance and accuracy assessment of the estimated results are important aspects in the AGB estimation procedure. In order to make comparisons between the field plots and the remotely sensed outputs, the field plots were assigned into four biomass

classes: < 50, > 50 < 100, > 100 < 200, and > 200 t/ha. The reclassification process of thematic biomass was conducted in the reclassify option under the ArcGIS spatial analyst tool. The accuracy of the output thematic maps was checked by four measures based on error matrices: producer's accuracy, user's accuracy, overall accuracy, and kappa statistics (Thapa and Murayama 2009) (Table 27). An overall accuracy of 60.18% and Kappa statistics of 0.42 were accepted for the thematic map resulting from multiple regression analysis.

Table 27: **Error matrix of biomass estimation by multiple regression analysis**

		Ground measured biomass (t/ha)					UA
	Class	1	2	3	4	Total	
Estimated biomass (t/ha)	1	14	0	0	0	14	100.00
	2	4	7	0	0	11	63.64
	3	4	2	6	1	13	46.15
	4	8	12	14	41	75	54.67
	Total	30	21	20	42	113	
	PA	46.6	33.3	30.0	97.6		

Notes: Class 1 = < 50 t/ha; Class 2 = > 50 < 100 t/ha; Class 3 = > 100 < 200 t/ha; Class 4 = > 200 t/ha; PA = producer's accuracy (%); UA = user's accuracy (%)

AGB estimation map

Multiple linear regression (MLR) analysis was used to develop AGB estimation models based on the integration of vegetation inventory data and remote sensing variables as described in the methodology section. Figure 63a shows the AGB estimation maps for the two reserved forests developed using MLR analysis, and Figure 63b after classification into the four biomass categories generated using the regression results. The estimated AGB ranged from 48.88 to 223.73 t/ha with a mean AGB of 140.89 t/ha, giving an estimated total of about 1.4 million tonnes (1,444,659 t) for the two reserved forests. The estimated areas of the individual biomass categories are shown in Table 28.

Table 28: **Area of individual biomass categories**

Biomass class (t/ha)	Area (ha)
< 50	217.8
> 50 <100	1,928.3
> 100 < 200	4,874.7
> 200	3,247.2
Total area	**10,268.0**

Discussion

The MLR AGB estimation using field inventory data and Landsat ETM showed that the most common biomass class in the two reserved forests was 100–200 t/ha. Although the highest biomass (t/ha) based on field inventory data was more than 400 t/ha, the highest biomass value generated by multiple linear regression was 224 t/ha. Other methodologies should be

Figure 63: **AGB estimation maps of the field study area (a) following multiple linear regression analysis and (b) after classifying into four biomass categories**
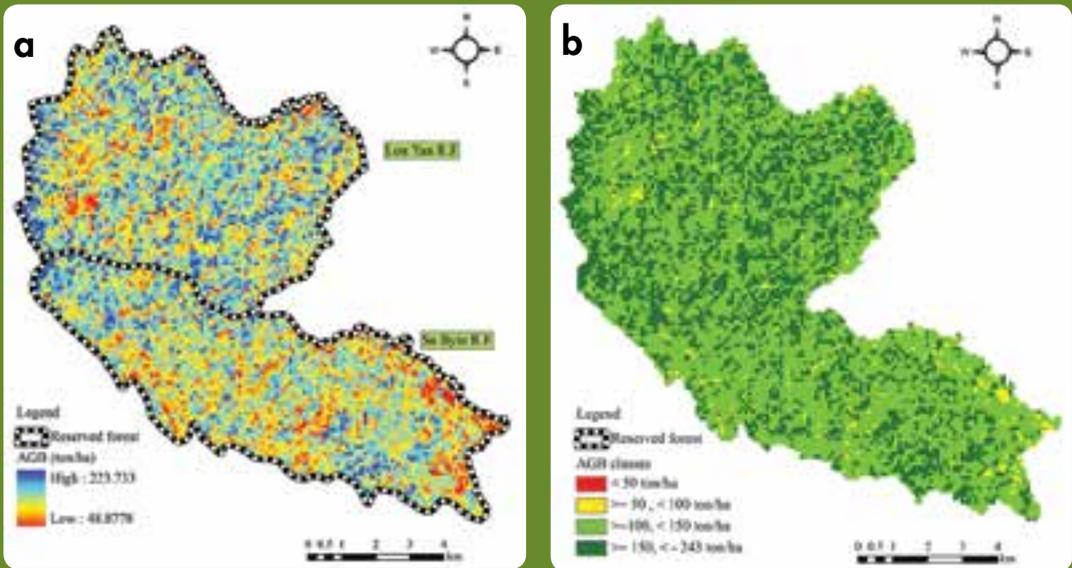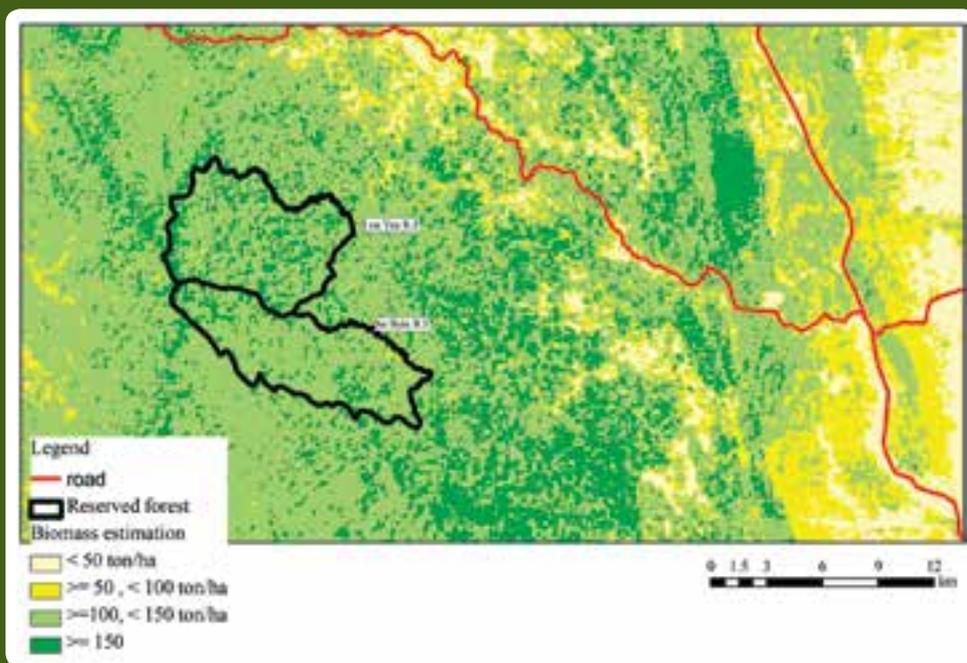
considered in future biomass calculations. The range of AGB values estimated in the two reserved forests of 49 to 224 t/ha was similar to the values found in other biomass studies of 126 t/ha in tropical forests of Canada, 144 to 182 t/ha in Brazilian rainforests (open), and 149 to 267 t/ha (Cummings et al. 2002).

Multiple regression analysis generated relatively high overall accuracy, kappa statistics, and user and producer accuracies for each class. More heterogeneous forest categories generate more complex patterns of spectral reflectance, which led to lower accuracies in the 50–100 t/ha class and 100-200 t/ha class in this study. Multiple regression analysis produced a 100% user's accuracy for the almost non-forest class, i.e., less than 50 t/ha AGB, and thus developed a difference between forest and non-forest categories. Figure 64 shows the AGB estimation for the reserved forests in the study and the neighbouring area.

Although the spectral reflectance of the Landsat image alone is not sufficient to deliver good results in estimating forest density in tropical mixed deciduous vegetation, it provided relatively good results in estimating AGB in this study. But we still need to test other methods and also different data sources. The limitation in spatial, spectral, and radiometric resolution inherent in remotely-sensed data is an important factor affecting AGB estimation performance. For example, a Landsat TM image with 30 m spatial resolution often contains many mixed pixels, with different tree species and vegetation ages in a single pixel. Multi-resolution data has a

potential for improving AGB estimation performance, but the time and labour involved in image processing is significantly increased. Economics is an important aspect of the use of multi-source remotely-sensed data over a large area.

AGB is calculated using allometric equations based on measured DBH and/or height, or from the conversion of forest stocking volume (Brown et al. 1989). These methods may generate major uncertainty because of the different purposes of field measurements, inconsistency of data collection dates, complex tree species composition, and different wood densities. Calibration or validation of the calculated AGB is necessary. A combination of spectral responses and image textures has proven useful in improving AGB estimation performance. The incorporation of remote sensing and GIS will also be useful in improving AGB estimation results when multi-source data are available.

Remote sensing techniques have many advantages in AGB estimation over traditional field measurement methods and provide the potential for estimating AGB at different scales. Therefore, future research may focus on the integration of multi-source data, which involves the effective integration of remote sensing (including optical and microwave data), GIS, and modelling techniques; a combination of multi-scale remotely sensed data, which involves the integration of field measurements with high (e.g. IKONOS), medium (e.g. Landsat TM/ETM+ and Terra ASTER), and coarse (e.g. MODIS and AVHRR) spatial-resolution data; and the

development of a suitable procedure for AGB estimation. The following factors should be considered to improve the accuracy of biomass estimation:

- Ground data collection time and image acquisition date should be considered as an important factor.
- This calculation depends only on a two-dimensional approach (spectral reflectance of the images); a three-dimensional approach including tree height (using aerial photos and Lidar data) should be used in order to increase the accuracy.
- Biomass estimation was conducted using a default equation developed from other regions; an allometric equation should be generated for the biomass equation.

Conclusion

Above ground biomass (AGB) of natural ecosystems is an important variable because it reflects the productivity of the land and as such can be used as an indicator for the degraded state (or otherwise) of the ecosystem. Furthermore, AGB is correlated with the carbon content of the vegetation species and is therefore useful for estimating the effectiveness of ecosystems as a carbon sink. Landsat imagery, which has the appropriate spectral and spatial resolution, relatively long historical datasets, and free worldwide data availability, has been extensively applied in forest biomass/carbon estimation. The integration of remote-sensing data with field surveys can provide estimates of biomass density in natural forest. This study was a preliminary study on estimation of forest AGB and may be useful in future estimations of AGB in other forest areas.

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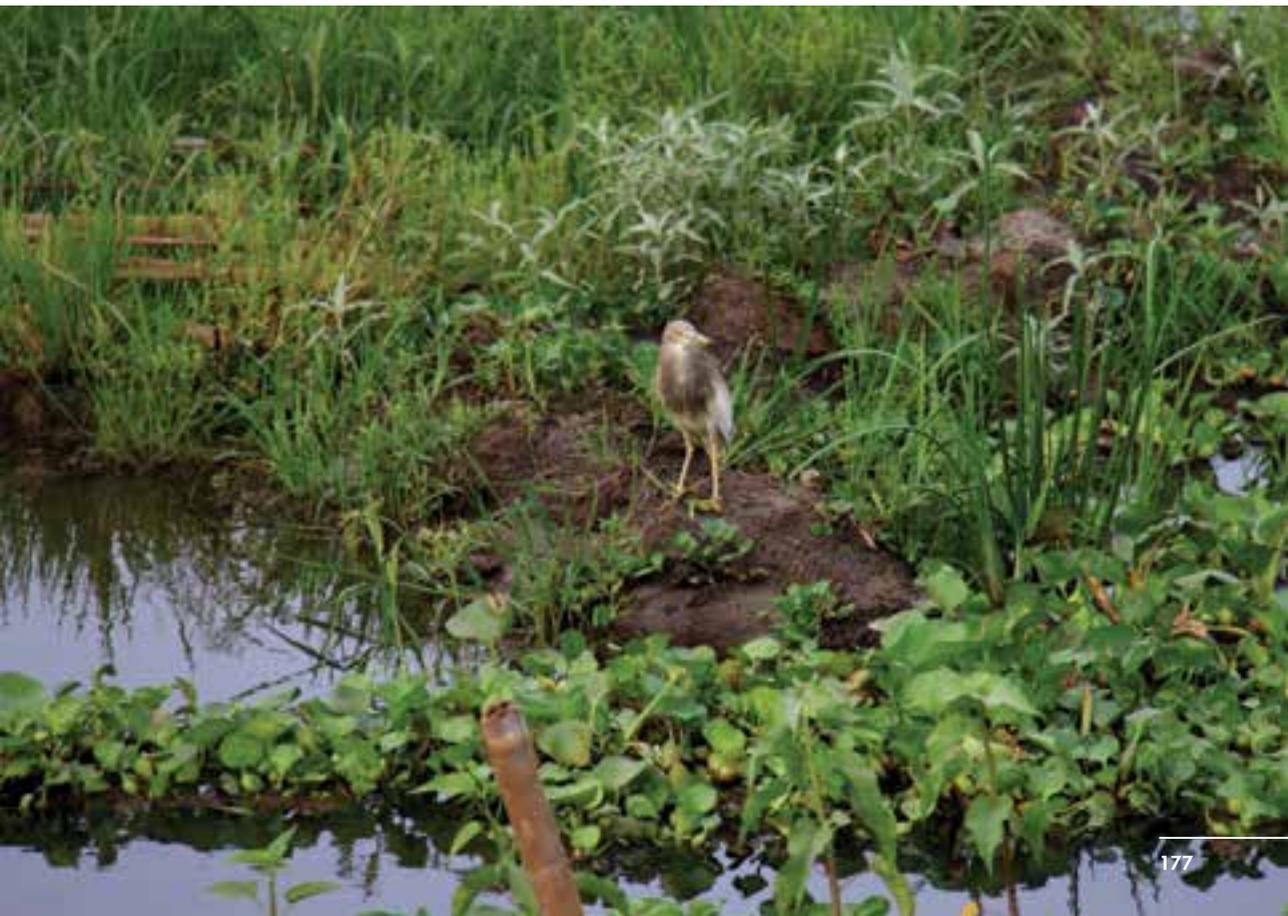
Forest Carbon Flux Assessment in Nepal Using the Gain-Loss Method

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*T*he land use, land use change, and forestry sector makes a major contribution to the greenhouse gas (GHG) inventory at the national level in Nepal. National communications submitted to the UNFCCC cover a large portion of the emission reports from agriculture, forestry, and other land use (AFOLU). The AFOLU data can be attributed using the land system information provided by land cover dynamics over time, e.g., 1990 and 2010. The activity data from the land use change analysis provides forest change dynamics data in terms of categories such as 'forest remaining as forest', 'forest converted to other land systems', and 'other land systems converted to forest' over time. This paper considers carbon flux assessment in Nepal using the gain-loss method and a geospatial approach with land use/land cover data. A regular spatial framework was developed and applied to the indicators used in carbon flux quantification using land use change data and national estimates of forest growth and resource demand.. Between 1990 and 2010, the Terai forest had a negative carbon flux of 1.64 Mt, and the High Mountains forest a positive uptake of 2.4 Mt; in total 2.07 Mt carbon was estimated to be taken up by the forest areas in Nepal. This type of study can be used in other geographical areas to support the national GHG inventory and reporting processes. The study could be improved in the future using higher depth data such as VDC level population, land cover data with more forest types, species level growth rates, and recent national forest inventory data.

Keywords: forest cover change, GHG, carbon flux, geospatial approach

Introduction

Land cover dynamics provide a basis for studying the ecosystem services generated from a forest over time, especially those related to carbon sequestration, forest growing stock, sustainable harvestable amount, and forest contribution to the national economy. Repeated land cover assessments over time provide a basis for analysis of the environmental, social, biophysical, livelihood, and economic services of a forest (Bajracharya et al. 2010).

The contemporary issues of climate change and mitigation of climate change impacts and forest cover and contribution to atmospheric carbon accumulation are major topics of discussion, nationally and internationally. Stern (2007) and IPCC (2006) state that forest acts as both a sink and a source of carbon emissions, and that at present forest contributes

approximately 18% of global GHG emissions. This led to the concept of payment for avoided deforestation and forest degradation and the Bali Action Plan, which endorsed the REDD+ mechanism, which extended the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) mechanism to include the role of conservation, sustainable management of forests and enhancement of forest carbon stocks, as a mitigation option. The approach of payment for the environmental services of forests in mitigating carbon emissions requires regular monitoring of the forest as well as a baseline for comparison of future forest restoration.

The population in Nepal is growing (CBS 2011); this and urban expansion are increasing the pressure on forests (MOPE 2004). The IPCC Guidelines (IPCC 2006) list agriculture, forestry, and other land use (AFOLU) as one of the contributors to global GHG emissions, with others including transportation, energy, and waste management. In line with these guidelines, Nepal's GHG inventory mainly focussed on five categories: energy activities; industrial processes; agriculture, land use change, and forestry; and waste management (MOPE 2004). The first national communication (2000) concluded that the net carbon emissions in Nepal from land use change and forestry were about 8,117 Gg in the base year 1994/95, after deduction of 14,738 Gg of carbon dioxide sequestered due to biomass growth.

Most of the countries in the Hindu Kush Himalayan region have provided a first (initial) national communication to the UNFCCC; very few countries have provided, and many are preparing, a second communication. However, there is a general lack of the relevant land cover change data and integration to develop forest cover change for use in the estimation of carbon flux. The present study aimed to apply the gain-loss method to estimate carbon fluxes due to forest cover changes in Nepal, making use of complete and consistent decadal land cover databases and developing a GIS-based customization to integrate field based emission factor data. Such a spatial framework and customized system will help the countries of the region in developing and improving estimates using a geospatial approach.

Methodology

Forest carbon flux estimation methods

There are two different methods for estimating changes in carbon stock: 1) the gain and loss method, which estimates the net balance of additions to and removals from carbon stock; and 2) the stock change method, which estimates the difference in carbon stock at two points in time.

Gain and loss method

In the gain and loss method, annual changes in carbon stocks are estimated by summing the differences between the gains and losses in a carbon pool. In growing stock, gains occur due to growth (increase of biomass) and due to transfers of carbon from another pool. Losses occur due to transfers of carbon from one pool to another including through processes such as decay, burning, or harvesting (e.g., the carbon in the slash during harvesting is a loss from

the above ground biomass pool). For each pool, the carbon stock change is calculated using the following equation:

$$\Delta C = \Delta CG - \Delta CL$$

where ΔC annual change in carbon stocks in the pool, tC/yr
        ΔCG annual gain of carbon in the pool, tC/yr
 ΔCL annual loss of carbon from the pool, tC/yr

Stock-change method

The stock change method can be used where carbon stocks in a pool are measured at two points in time. The following equation is applied:

$$\Delta C = (Ct_2 - Ct_1)/(t_2 - t_1)$$

where ΔC annual change in carbon stocks in the pool, tC/yr
        Ct_1 carbon stocks in the pool at time t_1, tC
        Ct_1 carbon stocks in the pool at time t_2, tC

The two methods give essentially the same result in terms of emissions, but differ in terms of effort (Bird et al. 2010). Figure 65 highlights the differences between the two methods.

Figure 65: **Approaches for estimating changes in carbon stock**

Source: Bhattarai et al. 2010
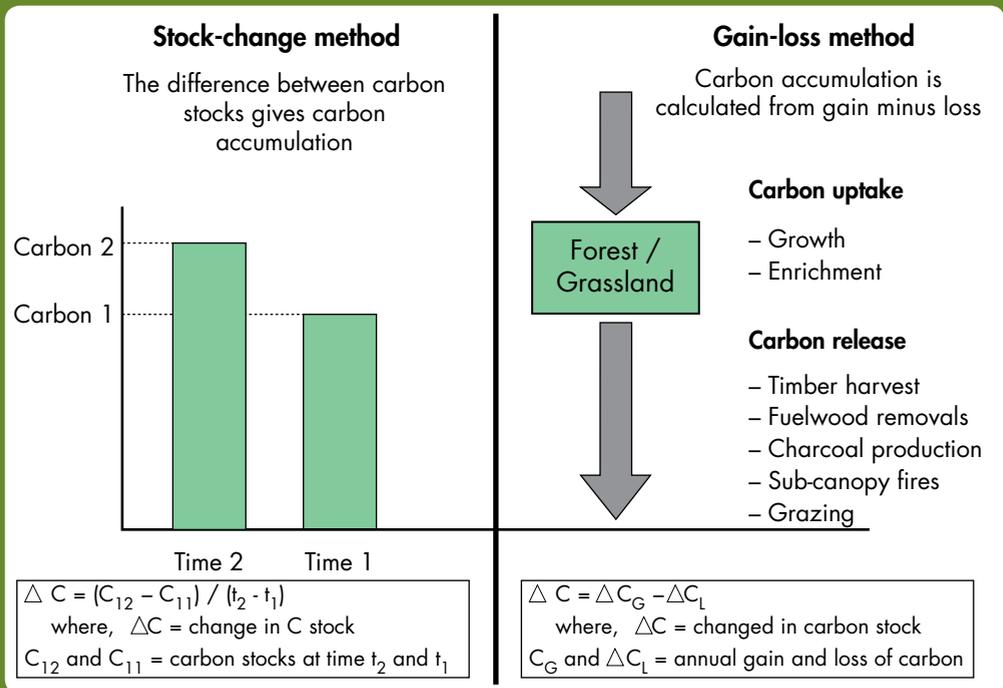
Study methodology

The study used the gain-loss method to estimate carbon flux, as there were no consistent repeated biomass inventories available for use in the stock change method. The gain-loss method has two components that are critical for estimating the carbon flux: the activity factor database and the emission factor database. The activity factor database addresses land cover change dynamics, while the emission factor database addresses biomass dynamics due to natural and anthropogenic systems. Hence the emissions estimates are based on data on land use change (activity data) multiplied by a factor that expresses the significance of this change in terms of GHG emissions. In essence this means the following:

Emission estimate = [emission factor] x [activity data]

Generation of activity data

IPCC (2006) describes three different approaches for generating activity data:
Approach 1: Total data are generated from a whole land-use area within a spatial unit, which is often defined by political boundaries such as a country, province, or municipality. Only the net change in land-use area can be tracked.

Approach 2: This approach provides an assessment of the net losses or gains of specific land-use categories within a defined area and what these conversions represent (i.e., changes both from and to a category). It includes information on conversions between categories, but is still not spatially explicit, and the location of specific land use and land-use conversions over time are not known.

Approach 3: This approach provides spatially-explicit observations of land-use categories and land-use conversions, often tracking patterns at specific point locations and/or using gridded map products that can be derived from remote sensing imagery. The data may be obtained by sampling or wall-to-wall mapping techniques or a combination of the two. The advantage of spatially explicit data is that analysis tools such as a geographic information system (GIS) can be used to link multiple spatially explicit datasets (e.g., those used for stratification) in order to describe the conditions of a particular piece of land prior to and after a land-use conversion in detail.

Land cover change databases for Nepal for 1990–2000–2010 were prepared using Landsat TM datasets under the SERVIR-Himalaya initiative (supported by NASA and USAID) (Uddin et al. 2015). Object-based image analysis (OBIA) techniques were used to give a better and more efficient classification. The approach used the Normalized Difference Vegetation Index (NDVI) for the interpretation of vegetation and other class segmentation, and other image indices such as Normalized Difference Snow Index (NDSI), Soil Adjusted Vegetation Index (SAVI), and Land Water Mask (LWM) for the interpretation of snow, land, water, and bare areas. In addition, ancillary digital information such as expert knowledge on forest types and

topographic information on altitude, slope, and aspect were also used to refine the classification rule sets used during the classification. The classification was verified and validated using field information from partners such as WWF and the Forest Resource Assessment (FRA) Project, among others. These consistent and systematic datasets formed a reliable base for the activity data used in the estimation of carbon flux in the study presented here (study used 1990–2010).

After finalization of the land cover classification for 1990 and 2010, spatial change analysis was carried out using a GIS overlay method. This operation essentially gave three outputs – forest cover remaining as forest cover, forest cover converted to other classes, and other classes converted to forest cover – which provided specific land cover information on forest cover changes over time.

The forest remaining as forest category can include both areas with regeneration and areas with degradation; however, drastic changes were not expected in these areas. The forest converted to other land use type reflects deforestation and is likely to be the main contributor to carbon emissions to the atmosphere from forest. The other land use types converted to forest category is likely to be the main contributor to the removal of atmospheric carbon over the time period.

Emission factors

IPCC (2006) has three tiers for categorizing methods to estimate emissions. The higher the tier number, the more rigorous the requirements for the data, the more complex the analysis performed, and hence, the more accurate the estimate.

Tier 1 uses default values for forest biomass and forest biomass mean annual increment (MAI) obtained from the IPCC Emission Factor Data Base (EFDB), which correspond to broad continental forest types.

Tier 2 uses country-specific data (i.e., data collected within national boundaries). Forest biomass is resolved at finer scales through the delineation of more detailed strata.

Tier 3 uses actual inventories with repeated measurements of permanent plots to measure changes in forest biomass directly. Well-parameterized models may be used in addition or instead, in combination with plot data. The Tier 3 approach requires a long-term commitment of resources, and generally involves establishing a permanent organization to house the monitoring programme (Herold et al. 2012); the results can be used for estimating carbon fluxes.

The present study used available data and published information mostly from national or region specific databases for the emission factors (Tier 2 level information). As there is a large
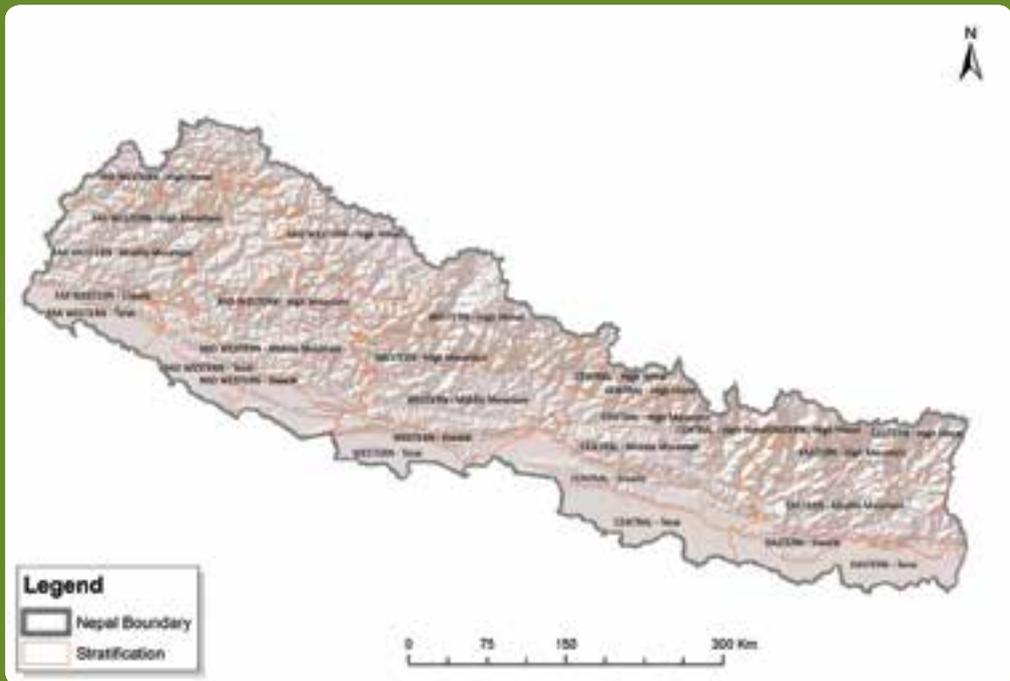
degree of heterogeneity in the climatic, topographic, and biotic regimes affecting carbon flux, an effort was made to use emission factor information that was as spatially explicit as possible. The country was divided into 25 functional strata based on five altitude and five development regions (Figure 66); wherever possible, the data were generated at the finest strata level, otherwise they were aggregated to the next coarsest level strata. The broad parameters, data used for emission factors, and tier level and strata level at which data were generated are given in Table 29. The carbon flux from the forest was estimated based on the parameters and equations described in the paper by Kaul et al. (2009).

Spatially explicit estimation

The land cover change product was generated at a spatial resolution of 30 m. The emission factor data generated at a broader strata level were also rasterized at 30 m grid resolution. This facilitated linking of the activity data layers (forest remaining as forest, forest to other, and other to forest) and the emission factor layers (biomass conversion, sustainable harvest, timber and wood removal, trees outside forest, mean annual increment, and conversion factors) and calculation of the carbon flux at 30 m resolution.

Table 29: **Variables used in the carbon flux analysis and their source**

| SN	Parameter	Source	Tier	Stratification
1	**Activity data**			
1.1	*Forest to forest*	ICIMOD estimates	2	Physiographic region, development region
1.2	*Forest to other*	ICIMOD estimates	2	Physiographic region, development region
1.3	*Other to forest*	ICIMOD estimates	2	Physiographic region, development region
2	**Gain**			
2.1	*Mean annual increment*	Kandel et al. 2012	2	Physiographic region
3	**Loss**			
3.1	*Timber removal*	Kandel et al. 2012	2	Physiographic region
3.2	*Fuelwood removal*	WECS 2010	2	Physiographic region
3.3	*Sustainable harvest*	WECS 2010	2	Physiographic region
4	**Uptake by abandoned land**	MOPE 2004	2	Physiographic region
5	**Trees outside forest**	Kandel et al. 2012	2	Physiographic region
6	**Soil**	MOPE 2004	2	Physiographic region
7	**Forest fire**	MODIS burnt area product	2	Physiographic region

Results and Discussion

Activity data: Land cover change analysis

The overall areas of the different classes of land cover Nepal in 1990 and 2010 are shown in Table 30, and the changes in individual classes in the form of a change matrix in Table 31. The spatial distribution of the land cover classes and change in forest cover are shown in Figure 67. Between 1990 and 2010, there was a decrease in forest cover as a percentage of total land area of Nepal from 40.2% (with 3.2% shrub) to 39.7% (with 3.1% shrub) and an increase in cultivated land from 28.6% to 29.7%.

Table 30: **Nepal land cover 1990 and 2010**

Class	Land cover 1990		Land cover 2010	
	km²	%	km²	%
Forest	59,537	40.2	58,754	39.7
Shrub	4,755	3.2	4,532	3.1
Grass	11,291	7.6	11,520	7.8
Agriculture	42,328	28.6	43,887	29.7
Bare land	14,862	10.0	15,489	10.5
Other	15,225	10.3	13,815	9.3

Figure 67: **Land cover change analysis from 1990 to 2010 in Nepal: a) land cover 1990; b) land cover 2010; c) forest cover change 1990–2010; d) remaining forest**
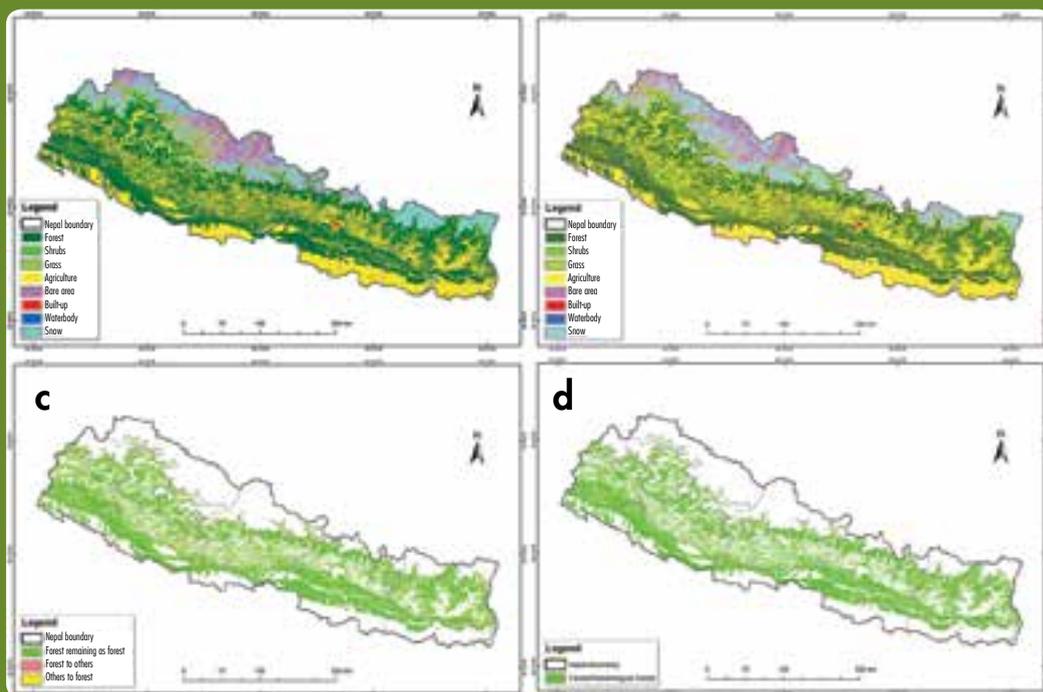
Data source: ICIMOD

Table 31: **Land cover change matrix for Nepal 1990 to 2010 (area in km²)**

Class	Forest	Shrub	Grass	Agriculture	Bare land	Other	Total 1990
Forest	58,065	397	158	797	63	57	59,537
Shrub	187	3,716	285	556	10	1	4755
Grass	206	114	8,051	528	756	1,636	11,291
Agriculture	194	75	85	41,471	434	69	42,328
Bare land	38	42	1,128	426	11,733	1,495	14,862
Other	64	189	1,814	108	2493	10,557	15,225
Total (2010)	**58,754**	**4,532**	**11,520**	**43,887**	**15,489**	**13,815**	**147,998**

In a previous study, the forest cover in Nepal was estimated to have decreased from 43% (with 5% shrub) in 1978 to 39.6% (with 10% shrub) in 1994 (LRMP 1986, DFRS 1999). This suggests that the deforestation and degradation rate has slowed considerably, although the values in the three studies are not strictly comparable as they were derived using different methodologies.

Forest cover change analysis was also done using the stratified 5 x 5 matrix based on development regions (5) and physiographic zones (5) (Figure 66). The stratified changes in forest cover are shown in Table 32. The middle mountains of the Western Development Region showed the biggest conversion both of forest area to other (495 km²), and of other to forest (387 km²). The western Terai showed the smallest conversion both of forest area to other (29 km²), and of other to forest (9 km²).

Table 32: **Forest cover change by development region and physiographic zone (area in km²)**

Physiographic zone and development region	Forest remaining as forest	Forest to other	Other to forest
High Himal			
Eastern	232.0	25.7	61.3
Central	225.8	16.7	18.0
Western	240.9	68.2	61.5
Mid-Western	274.6	32.1	32.7
Far-Western	71.6	12.1	38.5
High Mountains			
Eastern	3,466.7	139.8	199.0
Central	2,552.2	101.8	82.0
Western	2,859.1	230.8	192.9
Mid-Western	5,682.3	420.6	353.8
Far-Western	2,536.6	263.9	163.0
Middle Mountains			
Eastern	4,353.0	298.6	294.0
Central	4,711.2	286.4	239.1
Western	3,946.3	494.7	387.1
Mid-Western	3,406.4	479.6	301.5
Far-Western	3,621.9	192.6	156.9
Siwaliks			
Eastern	1,751.8	86.9	51.4
Central	4,407.2	111.4	94.6
Western	1,678.9	79.7	36.5
Mid-Western	3,746.7	120.7	99.6
Far-Western	1,689.3	52.6	35.4
Terai			
Eastern	507.3	87.5	19.0
Central	908.3	54.2	23.2
Western	399.9	29.2	9.4
Mid-Western	833.2	40.4	26.0
Far-Western	1,176.6	94.9	29.8

Forest carbon flux analysis

Table 33 shows the results of the estimation of forest carbon flux using the gain-loss method in each of the physiographic zones.

The carbon gain in a forest mainly comes from growth in forests that remain as forest, conversion of non-forest land to forest, and soil uptake. The Siwaliks and high mountains showed relatively high levels of carbon uptake. This was partly due to the large area of forest cover but is also thought to be the result of the community forest programme. Several studies have reported that community forestry, implemented in Nepal since 1990, has contributed to conservation and protection of forests.

The carbon loss in a forest depends on the withdrawal of fuelwood and timber, and conversion of forest to non-forest. The high level of carbon loss in the Terai region is the result of high levels of both wood extraction and deforestation. The net loss in the high Himal region is the result of unsustainable extraction resulting from the relatively small per capita area of forest and lack of alternative fuel resources.

Table 33: **Forest carbon flux in Nepal (1990–2010) (tonnes)**

Description	Uptake (removal from atmosphere)	Emission	Carbon flux
High Himal	114	-181,596	-181,482
High mountains	2,402,969	-757	2,402,212
Middle mountains	171,844	-124,741	47,103
Siwaliks	1,466,337	-19,471	1,446,866
Terai	585	-1,643,317	-1,642,732
Total	**4,041,849**	**-1,969,883**	**2,071,966**

Forest carbon flux map

The spatial distribution of carbon flux values was also mapped. Carbon flux was calculated as a function of the carbon flux in forest remaining as forest and in forest converted to other land systems, as well as carbon uptake in abandoned land and due to forest restoration. The spatial distribution of carbon gain, carbon loss, and total carbon flux in forest between 1990 and 2010 is shown in Figure 68. The net carbon uptake was estimated to be 2.07 Mt (Table 33). The high mountains and Siwaliks were the major carbon sinks and the Terai and High Himal the main sources of emissions.

Figure 68: **Carbon flux in Nepal (1990–2010): a) carbon gain; b) carbon loss; c) carbon flux**
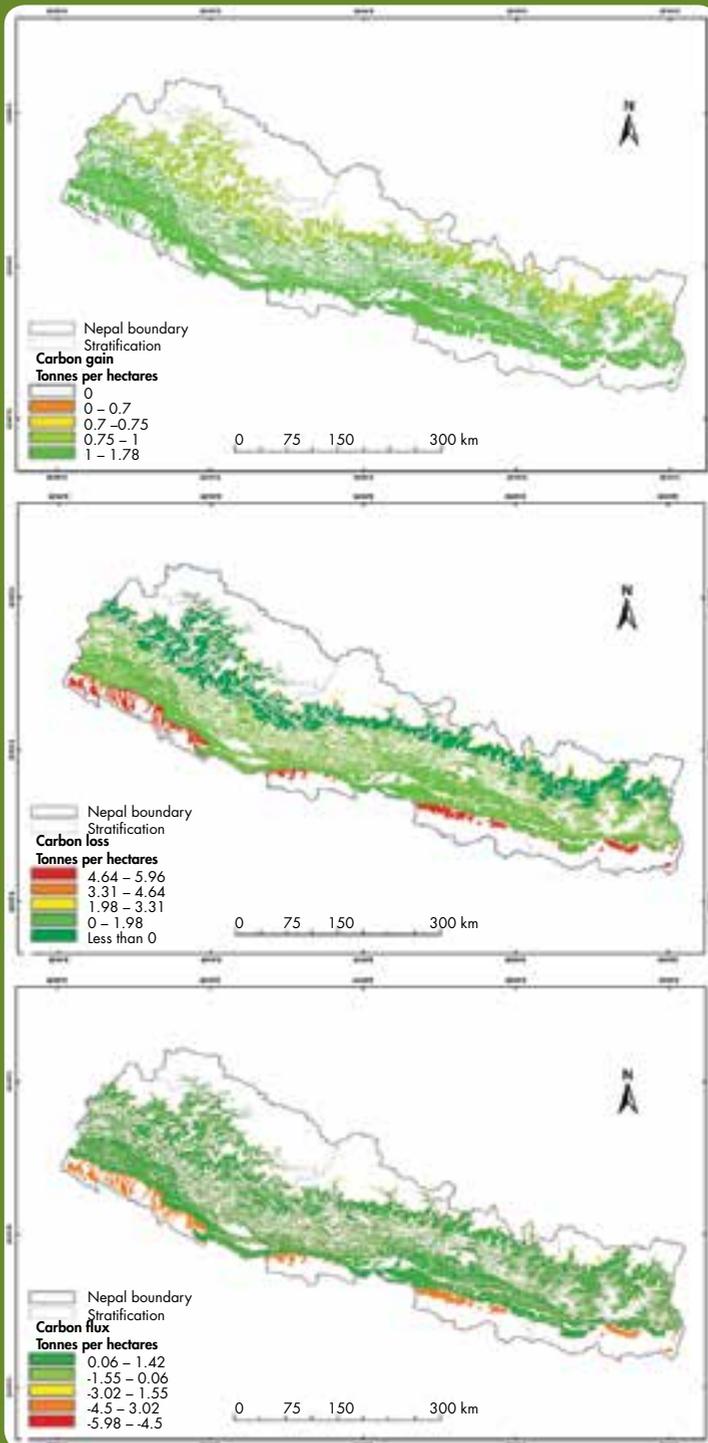
Source: ICIMOD

Conclusion

The use of available information from various documents at national level can support Tier 2 calculations of carbon flux using the gain-loss method by applying stratification in terms of development region and physiographic zone (elevation zones). The data and maps derived in this way can be used to provide more precise carbon flux estimations for national communications and national forest monitoring systems and for the formulation of national strategy on REDD+ activities such as reference emission level and monitoring, reporting, and verification.

Various improvements are being considered as a part of ongoing research efforts to improve the estimates. In the present study, changes in soil mineral carbon could not be taken into account due to the lack of sufficient information for 1990 and 2010. Carbon flux in other land converted to forest was also not quantified exactly due to the lack of information on emission factors for such areas. The use of growth rates for different forest types rather than for physiographic zones would also improve biomass gain estimates. Finally, VDC level population data and associated fuelwood demand would enable more spatially explicit calculation of extraction rates.

Acknowledgements

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Annex

Table A1: **Growth rates**

Physiographic zone	Annual Growth (t/ha)
High Himal forest	1.75
High mountains forest	1.64
Middle mountains forest	1.64
Siwaliks forest	2.34
Terai forest	2.34
Shrub	0.59
Grass	0.085

Table A2: **Conversion factors**

Physiographic zone	Wood density
High Himal	0.40
High mountains	0.45
Middle mountains	0.60
Siwaliks	0.76
Terai	0.72

Table A3: **Timber removal**

Physiographic zone	Timber removal (tonnes/yr)
High Himal	194,000
High mountains	1,013,519
Middle mountains	707,481
Siwalik	706,196
Terai	749,804

Table A4: **Fuelwood removal**

Physiographic zone	Fuelwood removal (tonnes/yr)
High Himal	548,765
High mountains	830,879
Middle mountains	3,516,662
Siwaliks	1,890,109
Terai	3,541,940

Table A5: **Sustainable yield**

Physiographic zone	tonnes/yr
High Himal	399,000
High mountains	2,708,999
Middle mountains	1,891,001
Siwaliks	1,395,988
Terai	1,482,192

Table A6: **Trees outside forest**

Geographic region	Number of trees			Annual growth rate (tonnes/yr)
	1990	2000	2010	1990–2000
Mountains	4,519,032	6,620,873	9,336,801	0.0389
Hills	29,685,585	47,540,657	72,632,801	0.0482
Terai	14,769,477	15,337,532	15,867,438	0.0038

Table A7: **Forest area destroyed by fire (ha/yr)**

Physiographic zone	Development region				
	Eastern	Central	Western	Mid-Western	Far-Western
High Himal	0	425	100	0	175
High mountains	0	0	275	500	550
Middle mountains	475	0	350	0	0
Siwaliks	100	0	2,375	0	0
Terai	0	0	1,000	0	775

Operational Scaling Up of Basal Area Methodology in a Sub-Tropical Forest in Nepal for REDD+ MRV

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Nearly 40% of Nepal's land area is forested. Although the current rate of deforestation is relatively low, it still needs improvement. Current forest policy and legislation classify the country's forests mainly according to their tenure or control, and especially community forest is considered to have been successful in restoring degraded sites. Detailed information is needed for planning further conservation and management strategies, and in particular, the proposed introduction of a mechanism for REDD+ (Reducing Emissions from Deforestation and Forest Degradation) and associated requirements for monitoring, reporting, and verification (MRV) requires detailed information on forest biomass and changes in carbon stocks. Remote sensing techniques, through different sensors and methods, offer a means for estimating forest above ground biomass (AGB). This paper describes a methodology developed for assessing forest basal area, and ultimately carbon stocks, for operational REDD+ MRV, using very high and medium resolution satellite datasets with a very limited number of field plots. A crown projection area (CPA) vs. basal area (BA) model was developed and validated at the watershed level. Open source base map imagery in Arcmap was used to collect data from virtual plots for scaling up at district level. The approach can considerably reduce field data requirements for estimation of biomass and carbon in comparison with inventory methods based on enumeration of all trees in a plot. The proposed methodology is very cost effective and can be replicated with limited resources and time. The virtual plotting techniques will be tested to confirm that the method can be used by local people (members of community forest user groups, foresters, and others) to obtain meaningful estimates of basal area and biomass in their forest areas for reporting purposes.

**Keywords:** REDD+ MRV, crown projection area, basal area, model, community forest

Introduction

In Nepal, 5.83 million hectares (40%) of the 14.7 million hectares of land is forested (DOF 2012). FAO (2010) reported that the annual rate of deforestation (1990–2010) in Nepal is relatively low, < 50,000 ha/year, but still needs improvement (Figure 69). The annual rate of

deforestation is highest in the Terai (1.6%), followed by the High Himalayas (0.97%), and the Siwalik Hills (0.87%) (Niraula et al. 2013). In terms of forest policy and legislation, the forests are classified in terms of the form of tenure or control as government-managed, community-managed, leasehold, religious, private, or protected (Acharya 2002). Government-managed and protected forests are directly administered by government agencies; community, leasehold, and religious forests are managed by local communities or user groups; and private forests are controlled by individual households (Singh and Chapagain 2006). A total of 1.65 million hectares of forest are controlled by communities (DOF 2012). The community forestry programme is generally regarded as having been successful not only in restoring degraded sites, maintaining biodiversity, and improving the supply of forest products, but also in forming local level institutions for resource management and improving the environmental situation (Niraula et al. 2013).

Detailed information is needed for planning conservation or management strategies, especially on properties such as species distribution, stand density, basal area, and canopy density that describe the forest vegetation and influence the forest biomass and thus the carbon stocks (Kim et al. 2010; Kwak et al. 2007; Lovell and Graetz 2001; Yang et al. 2013). FAO (2010) estimated the level of forest living biomass in Nepal in 2010 at 484 million tonnes (t) (359 million tonnes above ground biomass [AGB] and 126 million tonnes below ground biomass [BGB]), but these values are aggregated at the national level,

Figure 69: **Deforestation in Nepal**
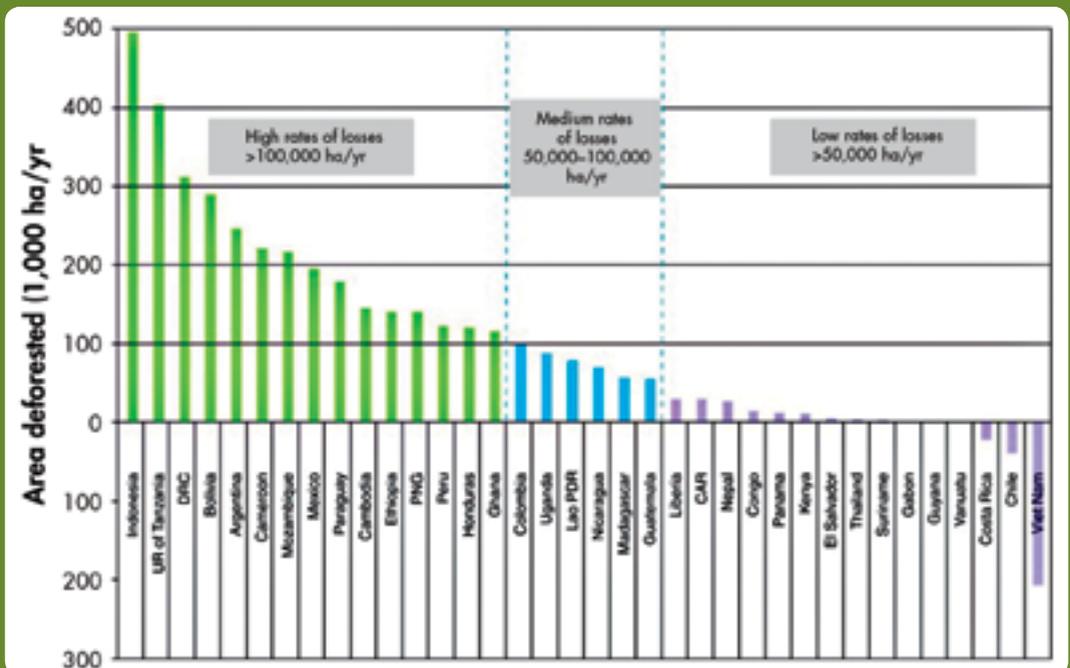
Source: FAO 2010 Global Forest Assessment Current Opinion in Environmental Sustainability

and not detailed enough to use for planning purposes. In particular, the proposed introduction of a mechanism for REDD+ (Reducing Emissions from Deforestation and Forest Degradation) and associated requirements for monitoring, reporting, and verification (MRV) requires detailed information on forest biomass and changes in carbon stocks.

Remote sensing techniques, using different sensors and methods, offer a means for estimating AGB. The advantage of using remote sensing data is that spatial distribution of forest biomass can be obtained at reasonable cost with acceptable accuracy (de Fries et al. 2007). A number of attempts have been made to estimate forest biomass and carbon stock using different platforms (air-borne and space-borne) and sensors (optical, radar, and Lidar) (Gibbs et al. 2007). Furthermore, several methods have been proposed for estimating forest biomass using remote sensing techniques that make use of a combination of regression models, vegetation indices, and canopy reflectance models (Cho et al. 2012; Gonzalez et al. 2010; Huang et al. 2013; Kajisa et al. 2009).

Medium and coarse spatial resolution datasets provide the potential for AGB estimation at national and regional level, but mixed pixels and data saturation pose a problem to estimation at sites with complex biophysical environments (Goetz et al. 2009). High spatial resolution data provide more accurate results than medium resolution data but are expensive and have less area coverage, thus they are not appropriate for use in operational REDD+ MRV in developing countries. Lu (2006) suggested that combining remotely sensed data derived at different scales (coarse to fine resolution) could improve the accuracy of AGB estimation at national and global scales. As a part of this, forest inventories are essential for quantifying the amount and distribution of carbon stocks, evaluating forests as a source of sustainable fuel (biomass for energy production), and conducting research on net primary productivity (Muukkonen and Heiskanen 2007). One of the important parameters in forest inventory is basal area (the area within a plot occupied by the cross-section of tree trunks and stems at breast height). The basal area of a tree can be derived from the tree diameter at breast height (DBH) and has a strong relationship with tree biomass and carbon stock (Balderas Torres and Lovett 2012).

This paper describes a methodology developed for operational REDD+ MRV using very high and medium resolution satellite datasets together with a very limited number of field plots. A crown projection area (CPA) vs. basal area (BA) model was developed and validated at the watershed level. The model developed for watersheds and community forest was used to assess the change over three years. Open source basemap imagery in Arcmap was used to derive data for virtual plots for scaling up at district level. Using this approach could considerably reduce the requirement for field level data for estimation of biomass and carbon in comparison with inventory methods based on enumeration of all trees in an area. The proposed methodology is very cost effective and can be replicated with limited resources and time. It is relatively straightforward and will be tested in the next stage of development to confirm that it can be used by local people (members of community forest user groups [CFUGs], foresters, and others) to obtain meaningful estimates of basal area and biomass in their forest areas for reporting purposes.

The specific objectives of the study were

- to develop and validate a CPA (delineated and extracted from satellite images) vs. BA (based on the field data) model;
- to quantify and compare BA maps using 2009 and 2010 GeoEye-1 VHRS images at the watershed and community forest level;
- to design virtual plots using open-source base-map imagery in Arcmap;
- to develop a multi-regression model for scaling up based on the virtual plot data and parameters extracted from remotely-sensed datasets; and
- to validate the regression model and carry out BA area mapping for the entire district.

Methodology

Study area

Chitwan District in Nepal was selected for the overall study, and within this the Kayer Khola watershed for detailed development of the model (Figure 70). The watershed has an area of 80 km², of which 23.81 km² is managed by 16 community forest user groups, while the whole district has an area of 2,218 km², which includes Chitwan National Park. The study area was selected on the basis of accessibility, data availability, variation in terrain, and ongoing implementation of a REDD+ pilot project.

Figure 70: **Location and map of the study area – Chitwan District and Kayer Khola watershed – showing position of field plots within the watershed and virtual plots within the district**

Legend

District boundary — District sample plots
Watershed boundary — Watershed samples
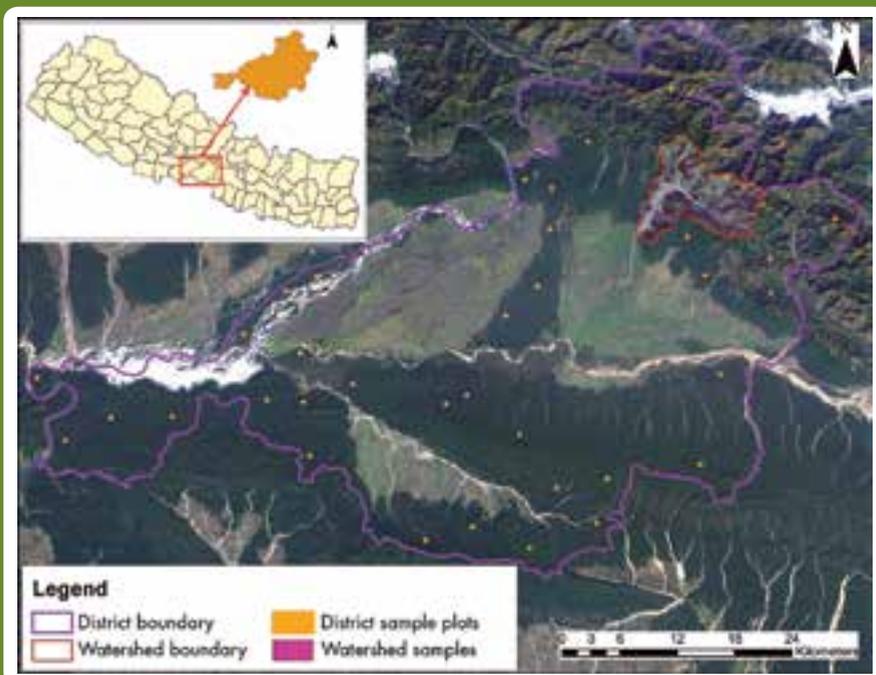
The district has mixed forests with the dominant species *Shorea robusta* (sal) found on most areas with a southern aspect and at the lower altitudes of areas with a northern aspect. *Schima wallichii* (chilaune) and a few associated species also thrive in the area.

Data and software

GeoEye-1 images captured on 2 November 2009 and 15 December 2012 were used for the watershed study. Both images were cloud and haze free. Landsat-8 Operational Land Imager (OLI) images from 2013 were used for scaling up at district level. Three images from 2013 were used captured in different seasons, on 15 April (summer), 30 May (rainy), and 9 and 18 November (winter), on row/path 142/041 and 141/41. A digital elevation model (DEM) was extracted from topographic sheets with a horizontal resolution of 30 m with extracted products like slope, aspect, and hill shade, to understand the topography of the area. An ordinary global positioning system (GPS) receiver was used for location identification in the field study, tree height was measured with a TruPulse 360B and DBH was measured with a measuring tape.

A total of 38 plots of 500 m^2 each within the watershed were used to develop the regression model; and a further 20 plots with the same area were used for validation. The position, height, and DBH of every tree with DBH > 5 cm in each plot were recorded. Thirty-five virtual plots of 1 ha (10,000 m^2) randomly distributed on a base map were generated for scaling up across the entire district.

The overall methodology is summarized in the form of a flow chart in Figure 71: the individual steps are described briefly in the following sections.

Pre-processing of remotely sensed data

Individual band-wise GeoEye-1 images were ortho-rectified using rational polynomial coefficient (RPC) files along a horizontal 20 m topographic DEM by applying a cubic convolution method in zone 44 of the Universal Transverse Mercator (UTM) coordinate system, with datum and spheroid from the World Geodetic System (WGS) 84. The spectral information at lower resolution (2 m) was merged with the high spatial resolution information (0.5 m) from the panchromatic image. The two GeoEye-1 images were independently ortho-rectified and fused with their respective multi and panchromatic spectral bands, but positional differences were observed when they were overlaid. To overcome this, 26 points were taken as ground control points (GCPs) in both datasets. This resulted in an overall root mean square error (RMSE) of 1.2 m for the panchromatic image and 1.5 m for the multispectral image. Prior to segmentation, low pass median filters are usually applied to avoid over-segmentation and smooth the appearance (Platt and Schoennagel 2009). In this study, convolution 3 × 3 low-pass filters were used to reduce local variation, remove noise, enhance tree features, and improve the quality of the analysed satellite images. The Landsat TM images were downloaded and a layer stack prepared to make multi-spectral images for visualization. The Normalized Difference Vegetation Index (NDVI) was extracted using the NIR and RED bands.

Figure 71: **Summary of the methodology**
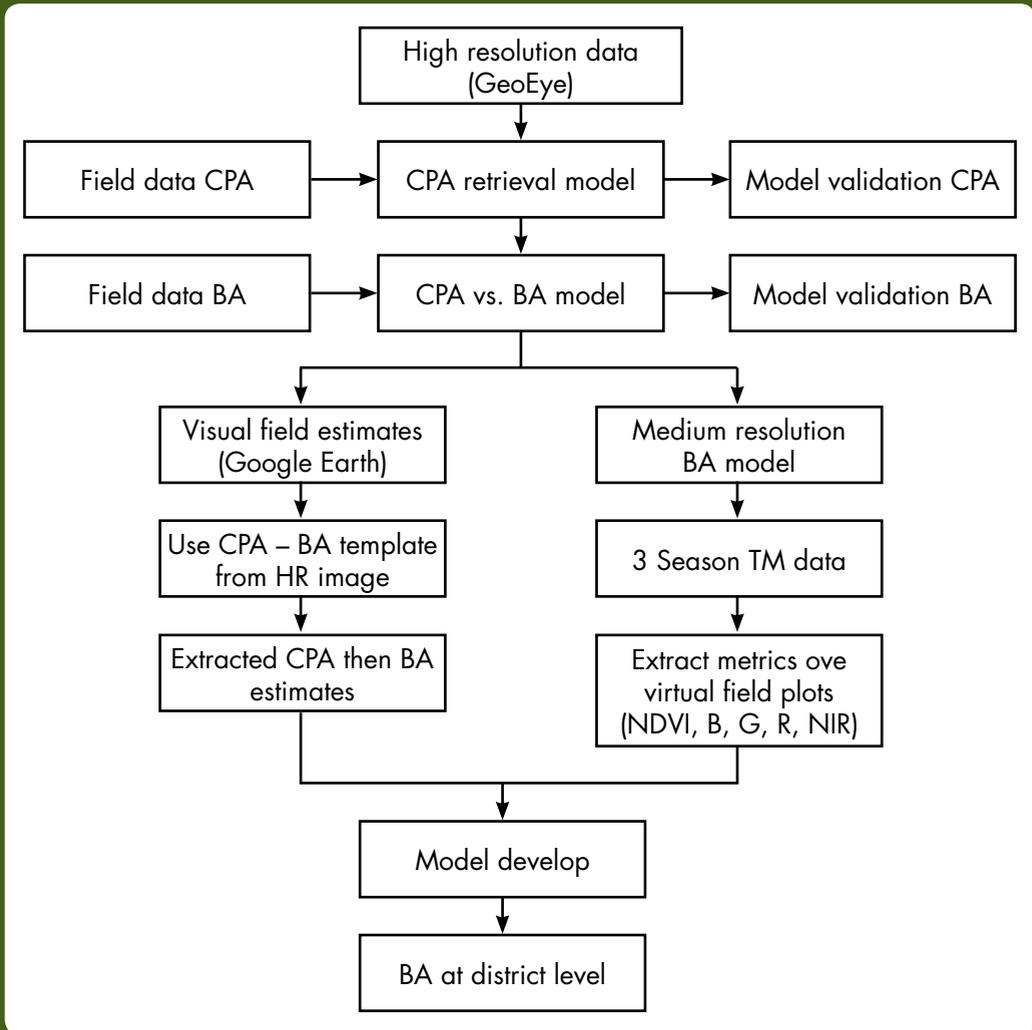
CPA delineation and development and validation of a regression model for BA comparison

Object based image analysis (OBIA) with a region growing technique was used for CPA delineation at the watershed level. In this method, tree tops are identified as maxima and the shadows between trees as minima. The segments are 'grown' from these maxima and the valleys act as boundaries (Figure 72). The first step in region growing was to create minimum size homogeneous objects through 'chessboard segmentation'; the brightest pixels were then identified as seed pixels (tree tops). Regions were 'grown' from the seed pixels up to the local minima, resulting in homogeneous objects based on predefined homogeneity criteria (Cui et al. 2008; Erikson 2003; Shih and Cheng 2005). Validation of the delineation was done using manually delineated tree crowns (visual interpretation of the images in a 1 ha grid).

Figure 72: **Delineation of crown projection area (CPA): a) satellite image, b) image with local maxima/tree tops, c) distance from tree tops**

The DBH (in centimetres) of each tree recorded in the field was converted into BA (m^2) and the values aggregated at plot level. In order to compare the results with the CPA extracted from satellite imagery using the region growing technique, the results from the 500 m^2 plots were multiplied to give the equivalent in 1 ha (10,000 m^2). The CPA was derived from the GeoEye-1 image of 2009 for the same plot areas using the region growing technique. A regression equation for the relationship between CPA and BA was derived and validated using the plot derived BA values and the image derived CPA values.

The spatial CPA across the whole watershed was derived from the GeoEye-1 images for each of the two years, and the spatial BA across the watershed calculated using the regression equation.

Template formation and BA identification at district level

A total of 35 virtual plots of 1 ha (10,000 m^2) randomly distributed on base map imagery of Arcmap were generated for scaling up from watershed to district level. The number of crowns and the crown area were observed in each plot by visual study of the image, and the BA value calculated using the regression equation, thus taking the diversity and different sizes of tree crowns into account.

A template was prepared for broadleaved forest showing the appearance of different ranges of CPA in the satellite image for the watershed before and after application of the seeding technique, and relating these to the BA value (Figure 73). This template was used to help identify crown size and CPA during the visual study of the virtual plots in the district in the Arcmap images.

The BA value for the district was derived using a multi-regression model which used the BA values for the virtual plots calculated from the CPA using the regression equation, together

with additional parameters extracted for each of the three seasons from the virtual plots in the Landsat images. The parameters used were blue, green, red, and near infrared reflectance, and NDVI values.

Results

CPA delineation and development and validation of the regression model for BA comparison

The CPA delineated through OBIA was compared with the CPA extracted manually within a 100 x 100 m grid for accuracy assessment. The results are shown in Figure 74; there was an 83% match (coefficient of determination $R^2 = 0.83$) between the values.

The CPA extracted from the satellite image of 2009 was compared with the BA derived from the DBH measured on the ground in the field plots. The two values showed a linear relationship with the coefficient of determination $R^2 = 0.76$ (Figure 75). The CPA was converted into a spatial map of BA for the entire watershed using the regression equation derived from the correlation (Figure 76). The extrapolated maps had an accuracy of 83% based on observed and predicted BA values.

The template (Figure 73) helped foresters recognize the variation in CPA in the basemap imagery from Arcmap. The spatial BA Classification and Regression Trees (CART) mapping model was used at the district level. CART is a non-parametric decision tree learning

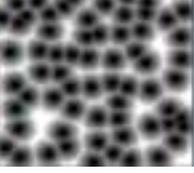Figure 73: **Template for reading the virtual plots**

Satellite image	Tree tops	Delineated crowns	CPA range (m²)	BA range (m²)
			9,600 – 9,800	3.2 – 3.9
			9,000 – 9,200	1.8 – 2.5
			8,800 – 9,000	0.4 – 1.1
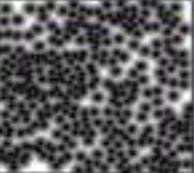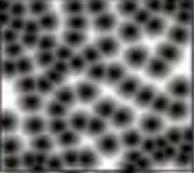
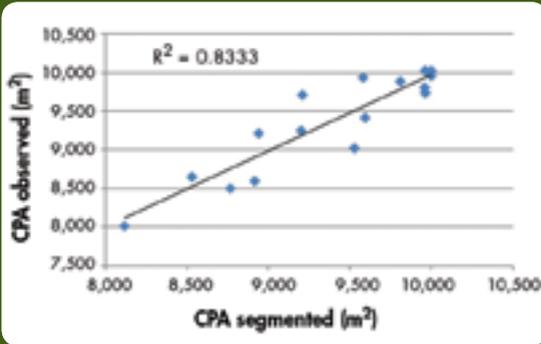Figure 74: **Validation of crowns delineated using the region growing technique**

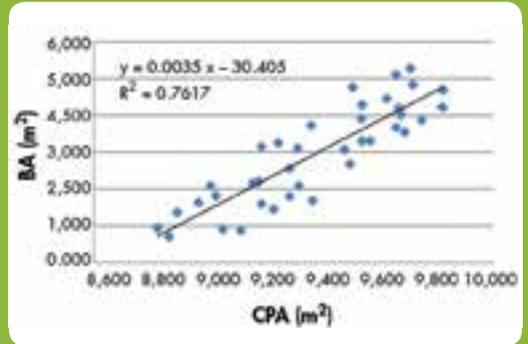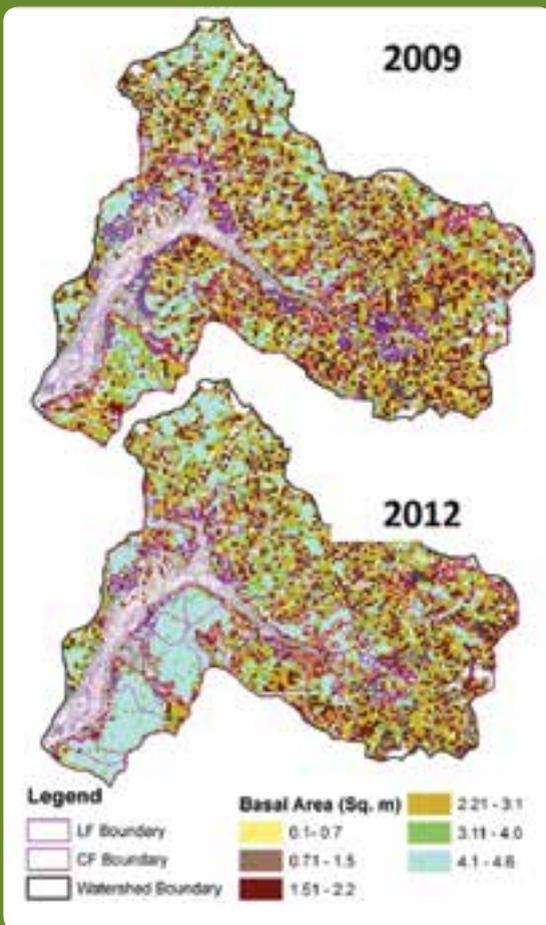Figure 75: **Linear regression between CPA and BA**

Figure 76: **BA maps of the watershed for 2009 and 2012**

technique that produces either classification or regression of trees, depending on whether the dependent variable is categorical or numeric, respectively. The CART model was used to extend the BA estimation to the entire district using 0.76 as the coefficient of regression. The results are shown in Figure 77.

Discussion and Conclusion

The study area is a natural broadleaf forest. The results show that the method of individual tree crown delineation using region growing was sufficiently flexible to detect tree crowns of different size. Ke and Quackenbush (2008) and Erikson and Olofsson (2005) also concluded that region growing is better than other algorithms. The methodology for BA mapping at both watershed and district level is convenient and easy to replicate. The template helped even those with limited knowledge of remote sensing to identify the number and area of tree crowns. This

Figure 77: **Basal area map for Chitwan District**
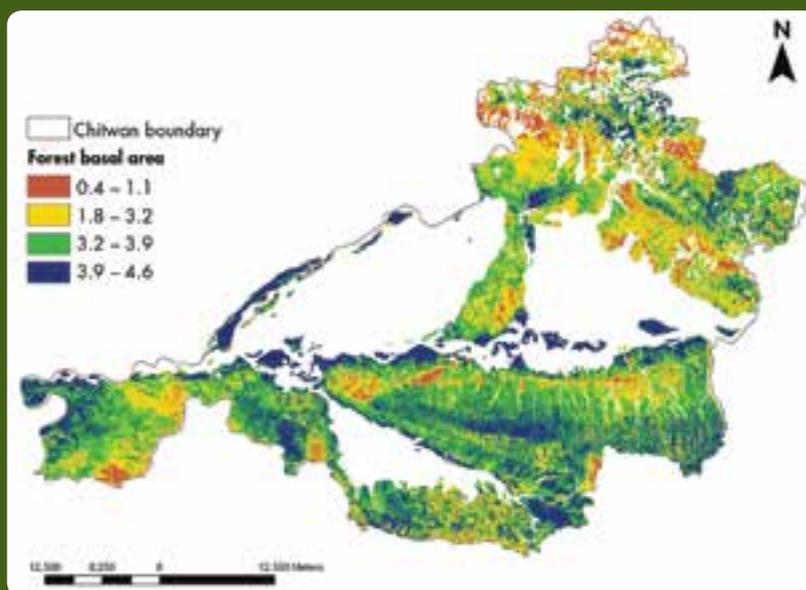
approach could considerably reduce the requirements for field data for estimation of biomass and carbon in comparison with inventory methods based on enumeration of all trees in an area. The method is suitable for pure broadleaved or coniferous forest, but could be less easy to use for mixed forests.

BA maps can be easily translated into biomass for carbon stock quantification. Balderas Torres and Lovett (2012) have explored different forms of allometric equations and analysed the potential for using equations for individual trees to derive stand-level equations, using the basal area and average diameter as explanatory variables.

The next step in this research will be to expand the methodology to other districts in Nepal. Instead of using commercial very high resolution satellite imagery, we are proposing to use less expensive imagery such as CARTOSAT-2.

Acknowledgements

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