II. LITERATURE REVIEW

2.1 Biomass and Carbon Stock

2.1.1 Definition of Biomass

Biomass was the name given to any recent organic matter that had been derived from plants as a result of the photosynthetic conversion process. Biomass is the mass (or weight) of living matter per unit area of ground. It is expressed in weight per unit area (ton or kg/ha). Between different vegetation types, biomass range from around 0.1 ton/ha for desert and 500 ton/ha for tropical rain forest. In the study of carbon budget, biomass is important because it directly represents the amount of carbon stored in living plants.

Aboveground biomass was difficult to quantify over large areas using traditional techniques and executed the relationship between LAI derived from NDVI and estimated aboveground biomass based on plant height. The aboveground biomass of the plant could be easily estimated with some accuracy from allometric relationship of trunk height (FAO 1997 in Thenkabail et al., 2002). Biomass ton per hectare depend on the plant height (regression with model LAI) and planting density.

Half of a tree mass is carbon, so large amounts of carbon are stored in plants and they are the largest carbon store of terrestrial carbon. In most ecosystems, most of carbon is stored below ground, either as roots and decaying biomass or as organic carbon in the soil. The tree carbon calculation used general allometric relationships to estimate aboveground biomass of the tree.
C-stock means the total carbon which stored in the biomass component and nekromass, above and inside soil (soil organic matter, plant root, and microorganism) per unit area of ground.

2.1.2 Biomass Estimation

Biomass, an estimate of the total living or dead organic material expressed as a weight per area (e.g. ton per hectare), has been the greatest interest when aggregated over regional conditions (Schroeder et al., 1997; Fang et al., 1998). For example, at the country scale of resolution, Brown et al. (1999) produced a map of density and pools of all forests in the eastern U.S by converting inventoried wood volume estimates of aboveground and belowground biomass. Combining these estimations with AVHRR satellite data produced map with 4x4 km grid cells: these products are useful, but are too coarse for many forest management purposes except the larger, strategic ones, for example, involving Kyoto report. Instead, spatially explicit estimates of stand or ecosystem biomass are now sought by managers as one component of the carbon cycling budget for a given forest, and as an input to important criteria and indicators of sustainable forestry such as percentage of biomass volume by general forest type (CCFM, 1997). Increasingly, biomass estimation is required at the stand level.

Traditionally, stand biomass estimates are derived by the same process as regional estimation of biomass, by conversion of stem volume estimates from the forest inventory database (Aldred and Alemdag, 1988). In less-well-inventoried areas of the world, biomass estimates may be developed through forest cover type volume tables (Brown and Lugo, 1984). The estimate begins with single tree estimates by species and site types. The appropriate local allometric equations are
developed to partition the estimate into foliar, branch, stem and root biomass estimates, or perhaps into two components: aboveground and belowground woody biomass components (Lavigne, Luther, Franklin and Hunt, 1996). A recent strategy is to develop a large-scale system for biomass estimation. Such an approach assumes that better biomass estimates can be generated by referencing all available information in a multistage approach: the forest inventory, the available satellite and airborne imagery, and data collected in the field in permanent sample plots (Czaplewski, 1999; Fournier et al., 1999).

2.1.3 Methods for Estimating Biomass Density from Existing Data

There are two main approaches for estimating the biomass density of woody formations based on existing data. The first approach is based on the use of existing measured volume estimates (VOB per ha) converted to biomass density (ton/ha) using variety of “tools” (Brown et al. 1989, Brown and Iverson 1992, Brown and Lugo 1992, Gillespie et al. 1992). The second approach directly estimates biomass density using biomass regression equations. These regression equations are mathematical function that relates oven-dry biomass per tree as a function of a single or a combination of tree dimension. They are applied to stand tables or measurements of individual trees in stands or in lines (e.g. windbreaks, live fence posts, home gardens). The advantage of this second method is that it produces biomass estimates without having to make volume estimates, followed by application of expansion factors to account for non-inventoried tree components. The disadvantage is that there is a smaller number of inventories report stand tables to small diameter classes for all species. Thus, not all countries
in the tropics are covered by these estimates. To use either of these methods, the
inventory must include all tree species. There is no way to extrapolate from
inventories that do not measure all species (Brown, 1997).

2.1.3.1 Approach 1: Biomass Density based on Existing Volume Data

This method is based on existing volume per ha data and is best used for
secondary to mature closed forest only, growing in moist to dry climate. It should
be used for closed forest only because the original data base for developing this
approach was based on closed forest. The primary data needed for this approach is

Volume over bark (VOB)/ha, that is inventoried volume over bark of tree bole
(Brown, 1997).

**General equation**

Biomass density can be calculated from VOB/ha by first estimating the
biomass of the inventoried volume and then expanding this value to take into
account the biomass of the other aboveground components as follows (Brown and

\[
\text{Above ground biomass density (ton/ha)} = \text{VOB} \times \text{WD} \times \text{DEF}
\]

Where:  
WD = volume weighted average wood density (t/ha of oven-dry
biomass per m\(^3\) green volume  
BEF = biomass expansion factor (ratio of aboveground oven-dry
biomass of trees to oven-dry biomass of inventoried volume)

**Volume Weighted Average Wood Density (WD)**

Wood density is defined as the oven-dry mass per unit of green volume
(either ton/m\(^3\) or grams/cm\(^3\)). Few data on wood density for trees in tropical
Africa and Asia are expressed in units of mass of wood at 12% moisture content
per unit of volume. A regression equation was developed by Reyes et al. (1992) to
convert wood density based on oven-dry mass and green volume.

\[ Y = 0.0134 + 0.800 \times X \quad (r^2 = 0.99) \]

Where:  
\( Y \) = wood density based on oven-dry mass/green volume  
\( X \) = wood density based on 12% moisture content

**Biomass Expansion Factor (BEF)**

Broadleaf forests: Biomass expansion factor is defined as the ratio of total aboveground oven-dry biomass density of trees with a minimum DBH of 10 cm or more to the oven-dry biomass density of the inventoried volume.

\[ BEF = \exp\{3.213 - 0.506 \cdot \ln(BV)\} \text{ for } BV < 190 \text{ t/ha} \]
\[ 1.74 \text{ for } BV \geq 190 \text{ t/ha} \]

Where:  
\( BV \) = biomass of inventoried volume in t/ha, calculated as the product of VOB/ha (m\(^3\)/ha) and wood density (t/m\(^3\))  
(sample size=56, adjusted \( r^2 = 0.76 \))

2.1.3.2 **Approach 2: Biomass Density based on Stand Tables**

Another estimate of biomass density is derived from the application of biomass regression equations to stand tables. The method basically involves estimating the biomass per average tree of each diameter (diameter of breast height, DBH\(^1\)) class of stand table, multiplying by the number of trees in the class, and summing across all classes (Brown, 1997).

**Biomass Regression Equations**

The biomass regression equations for broadleaf forests were developed from a database that includes trees of many species harvested from forest from all three tropical regions (a total of 371 trees with a DBH ranging from 5 to 148 cm).

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\(^1\) Diameter breast height (DBH) is a standard method of expressing the trunk diameter of the tree, measuring at 1.3 m above ground
from ten different sources) (Brown, 1997). The biomass regression equations can provide estimates of biomass per tree. The data base was stratified into main climatic zone, regardless of species: dry or where rainfall is considerably less than potential evapotranspiration (e.g. <1500 mm rain/year and dry season for several months), moist or where rainfall approximately balances potential evapotranspiration (e.g. 1500-4000 mm rain/year and a short dry season to no dry season), and wet or where rainfall is in excess of potential evapotranspiration (e.g. >4000 mm rain/year and no dry season). Table 2.1 depicts the regression models for estimating biomass of tropical trees based on rainfall climatic zone, as the research result conducted by Brown, Gillespie and Lugo (1989) in MacDicken (1997).

The linear regression equation approach requires the selection of the regression equation that is best adapted to the conditions in the study area. Linear regression models have been fitted to data in various situations of variable site and ecological conditions globally.

Table 2.1 Biomass regression equations for biomass estimation of tropical trees.

<table>
<thead>
<tr>
<th>Climate type based on annual rainfall</th>
<th>Equation</th>
<th>$R^2$ Adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry (&lt;1500 mm)</td>
<td>$Y = 34,4703 - 8,0671D + 0.6589D^2$</td>
<td>0.67</td>
</tr>
<tr>
<td>Moist (1500-4000 mm)</td>
<td>$Y = 38,4908 - 11,7883D + 1.1926D^2$</td>
<td>0.78</td>
</tr>
<tr>
<td></td>
<td>$Y = \exp[-3,1141 + 0.9719 \ln(DH)]$</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>$Y = \exp[-2.4090 + 0.9522 \ln(D^2S)]$</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>$H = \exp[1.0701 + 0.5677 \ln D]$</td>
<td>0.61</td>
</tr>
<tr>
<td>Wet (&gt;4000 mm)</td>
<td>$Y = 13,2579 - 4,8945D$</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td>$Y = \exp[-3,3012 + 0.9439 \ln(D^2H)]$</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td>$H = \exp[1.2017 + 0.5627 \ln D]$</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Where:  
$Y$ = Biomass/plant (kg)  
$D$ = Diameter at Breast height (cm)  
$H$ = Height (m)  
$S$ = Wood density (ton/m$^3$)
Table 2.2 Estimation of tropical forests biomass using regression equations of biomass as a DBH function.

<table>
<thead>
<tr>
<th>Restrictions: DBH and climate based on annual rainfall</th>
<th>Equation</th>
<th>( R^2 )</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 &lt; DBH &lt; 40 cm Dry transition to moist (rainfall &gt; 900 mm)</td>
<td>( Y = \exp{-1.996 + 2.32 \times \ln(DBH)} )</td>
<td>0.89</td>
<td>FAO</td>
</tr>
<tr>
<td>3 &lt; DBH &lt; 30 cm Dry (rainfall &lt; 900 mm)</td>
<td>( Y = 10^{-0.535 + \log_{10}(p \times r^2)} )</td>
<td>0.94</td>
<td>FAO</td>
</tr>
<tr>
<td>DBH &lt; 80 cm Moist (1 500 &lt; rainfall &lt; 4 000 mm)</td>
<td>( Y = \exp{-2.134 + 2.530 \times \ln(DBH)} )</td>
<td>0.97</td>
<td>FAO</td>
</tr>
<tr>
<td>DBH &gt; 5 cm Dry (rainfall &lt; 1 500 mm)</td>
<td>( Y = 34.4703 - 8.0671 \times DBH + 0.6589 \times DBH^2 )</td>
<td>0.67</td>
<td>Winrock (from Brown, Gillespie and Lugo, 1989)</td>
</tr>
<tr>
<td>DBH &gt; 5 cm Moist (1 500 &lt; rainfall &lt; 4 000 mm)</td>
<td>( Y = \exp{-3.1141 + 0.9719 \times \ln(DBH^2)H} )</td>
<td>0.97</td>
<td>Winrock (from Brown, Gillespie and Lugo, 1989)</td>
</tr>
<tr>
<td>DBH &gt; 5 cm Moist (1 500 &lt; rainfall &lt; 4 000 mm)</td>
<td>( Y = \exp{-2.4090 + 0.9522 \times \ln(DBH^2)H} )</td>
<td>0.99</td>
<td>Winrock (from Brown, Gillespie and Lugo, 1989)</td>
</tr>
</tbody>
</table>

Source: FAO document “Assessing carbon stocks and modeling win-win scenario of carbon sequestration”

Where: \( p = 3.1415927 \)
\( r = \) radius (cm)
\( DBH = \) diameter at breast height (cm)
\( H = \) height (m)
\( BA = J \times r^2 \)
\( S = \) wood density (0.61)

The work done by Brown, Gillespie and Lugo (1989) and FAO (1997) on estimation of above ground biomass of tropical forests using regression equations of biomass as a function of DBH is central to the use of this approach. DBH is used in estimating the amount of wood volume is a stand of trees (White 1998 in FAO). Some of the equations reported by Brown, Gillespie and Lugo (1989) have become standard practice because of their wide applicability. Table 2.2 presents a summary of the equations, as found in the specialized literature, including the
restrictions placed on each method.

2.1.3.3 Approach 3: Biomass Estimation from GIS Modeling

The approach for estimating biomass density based on modeling method with GIS (Geographic Information System) technology uses various existing digital data bases and maps of reliable inventories, population, density, climate, vegetation, ecofloristic zones, soils and topography. This method was developed as a means to extrapolate reliable inventory data that is generally limited in area coverage to biomass density estimates at larger scales such as continents (Brown, 1997).

Forest biomass density has been modeled in a multi-stage approach using GIS software packages and a variety of spatial and statistical data base. For estimating forest biomass density using GIS, the present distribution of forest biomass density was assumed to be based on the potential amount that the landscape can support under prevailing environmental conditions, and the cumulative impact of human activities on forests that reduce it biomass density. Many spatial data layers have been developed from existing data bases or were prepared by specialist (FAO, 1993 in Brown 1997). These data layers were entered into a GIS and processed according to specifications of the model.

The first step in this analysis was to estimate a potential biomass density (PBD) for forests. This was accomplished by first developing an index of potential biomass density based on climatic, edaphic and topographic factors. The potential biomass density map was masked with a forest map, produced by reclassifying all the forest classes of the vegetation maps into one forest class. The potential biomass density index (PBI) was calculated according to a simple model.
based on overlaying the following GIS data layers:

\[ PBI = \text{climatic index} + \text{precipitation} + \text{soil (texture, depth, slope)} + \text{topography} \]

Each of these factors was spatially represented by a numerical scale whose values were ranked according to how the particular factor affected forest biomass. The digital maps were overlain according to the above model and the results calibrated and validated using existing forest inventories for mature forests.

The final step was to add the influence of all human activities that result in a reduction of biomass of forests. This step was accomplished by using the biomass estimates from reliable forest inventory data. The first step was to calculate degradations ratios, defined here as biomass density estimations from the inventories (representing all forests of a sub-national unit) divided by the potential biomass for all forest in the same sub-national unit.

2.1.3.4 Approach 4: Biomass Estimation with Field Studies and Remote Sensing

A more comprehensive and reliable approach for estimating biomass change is to combine a new field studies with analysis of high resolution remote sensing imagery. The remote sensing efforts would be used to delineate forests into various distinct biomass strata. Then using statistical design, permanent plots in these forest strata could be established. For estimating biomass directly, stand tables are sufficient with use of the generic biomass regression equations. At least two measurements on permanent plots are needed to estimate biomass change. These measurements should preferably be a minimum of 5 year apart, particularly in forest vulnerable to change (Brown, 1997 and Hairiah et al, 2001).
2.1.4 Carbon Stock

Carbon stock is the amount of carbon which is stored in the biomass component and necromas above and below soil surface (soil organic content, plant root and microorganism) per unit area of land (Hairiah et al., 2003). The unit is in Mg ha\(^{-1}\) (mega gram per ha = ton per ha). One of the important functions of the forest is as the terrestrial carbon stock, because carbon is stored in the form of vegetation biomass.

2.1.5 Carbon stock measurement

2.1.5.1 Aboveground C: Allometric relation for trees

A major proportion of the C and nutrients in terrestrial ecosystem is found in the tree component. To reduce the need for destructive sampling, biomass can be estimated from an easily measured property such as stem diameter at a specified height, by using an allometric equation. Such equations exist for many forest types and a small number are species specific (Hairiah et al., 2001). Destructive measurement of trees (cutting down and weighting) to generate allometric equations, which have high precision needs a lot of labor and time, but when it is done it can be applied to other tree species in the same forest area. A substantial number of allometric equations have been developed for various climatic zones, forest types and tree species (Brown, 1997), using a variety of algebraic forms and parameter values.

The calculation of carbon stock as biomass consists of multiplying the total biomass by a conversion factor that represents the average carbon content in biomass. It is not practically possible to separate the different biomass components in order to account for variations in carbon content as a function of
the biomass component. Therefore, the coefficient of 0.55 for the conversion biomass to C, offered by Winrock (1997), is generalized here to conversions from biomass to carbon stock:

\[ C = 0.55 \times \text{biomass (total)} \]

This coefficient is widely used internationally, thus it may be applied on a project basis. The results may be displayed in a similar fashion to total biomass.

Carbon stocks of natural forests in Southeast Asia Using GIS, Brown et al., (1993) estimated that in 1980 the Winrock (1997) average C density of tropical forests in Asia was 144 ton C/ha in biomass and 148 ton C/ha in soils (up to 100 cm), which corresponds to total estimates of 42 and 43 Pg C for the whole continent, respectively. It was noted that C densities and pools in vegetation and soil varied widely by eco-floristic zone and country. Actual biomass C densities range from less than 50 to more than 360 ton C/ha with most forests having 100-200 ton C/ha.

A similar study reported an average maximum aboveground biomass C stock in forest lands in tropical Asia of 185 ton C/ha with a range of 25 to more than 300 ton C/ha. Palm et al. (1993), as reported by Houghton (1991), showed that the forests in tropical Asia have C densities between 40-250 ton/ha and 50-120 ton/ha in vegetation and soils, respectively. Southeast Asian forests have an aboveground biomass range of 50-430 ton/ha (25-215 ton C/ha) and >350-400 ton/ha (175-200 ton C/ha) before human incursion (Brown et al., 1991). For national GHG inventories, the IPCC (1997) recommends a biomass density default value of 275 ton/ha (or 138 ton C/ha) for wet forests in Asia.

There are limited data on C densities of natural forests in the specific
Southeast Asian countries. Indonesian forests have been estimated to have a C density ranging from 161-300 ton C/ha in aboveground biomass (Murdiyarso and Wasrin, 1995), 150-254 ton C/ha in above ground biomass and upper 30 cm of soil (Hairiah, et al., 2000) and 390 ton C/ha in above ground biomass and below ground pools (Hairiah and Sitompul, 2000).

2.1.5.2 Below ground C: root biomass

Root are an important part of the C cycle because they transfer large amounts of C directly in to the soil, where it may be stored for long time. Most of below-ground biomass of forest is contained in coarse roots (>2mm diameter), but most of that of annual crops is allocated to fine roots. Similar to approach for above ground biomass via allometric relations based on stem diameter, the below ground biomass can be estimated from the proximal roots at the stem base. The theoretical basis for this relationship is found in the fractal branching properties of root system (van Noordwijk and Purnomosidhi, 1995).

2.1.5.3 Belowground C: Soil Organic Matter

Soil organic matter content at any point in time is the result of organic inputs and the past rates of decomposition, as determines by inherent properties of the soil and the vegetation or land use system of the site. There are large differences in C storage capacity of soil related to: soil texture, landscape position and degree of drainage, mineralogy and physical disturbance.

2.2 Remote Sensing

Remote sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data required by a device that is not in contact with the object, area or phenomenon under investigation
2.2.1 Remote Sensing Application in Forestry

Application of remote sensing to sustainable forest management are presented in four categories that include classification of forest cover type, estimation of forest structure (inventory mapping), forest change detection and forest modeling. The inventory mapping of forest covers the measurement of cover, age, DBH, height, biomass, volume and growth (Franklin, 2001). Users in many countries adopt the remote sensing in many applications in forestry. These applications include forest cover type characterization, determination of forest stand conditions and forest health, site characterization and fire monitoring (Wynne and Carter, 1997). In India use remote sensing for plantation inventory and monitoring, timber volume estimation, species identification, estimation of biomass and productivity and biodiversity monitoring (Raa et al., 1997).

Table 2.3 listed the most system provide observation from a single sensors in either optical (e.g. Landsat, SPOT, IRS) or microwave (e.g. Radarsat, ERS-1) portion of the spectrum; occasionally a satellite will carry both types of sensor (e.g. ALMAZ). A few systems have thermal detectors or other sensors as part of the package but, in essence, the choice of a platform/sensor package in support of forestry applications has been limited in the past to a few satellites with quite similar characteristic in the optical or microwave portions of the spectrum (Franklin, 2001).
Table 2.3 Characteristic of selected existing and proposed satellite platforms and sensors for forestry.

<table>
<thead>
<tr>
<th>Identification</th>
<th>Sensor</th>
<th>Numb. of band</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Current Operational Satellites (Year 2000)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Landsat-5</td>
<td>TM, MSS</td>
<td>7, 4</td>
<td>30-120, 80</td>
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<tr>
<td>Landsat-7</td>
<td>ETM+</td>
<td>7</td>
<td>15-30</td>
</tr>
<tr>
<td>SPOT-2</td>
<td>HRV</td>
<td>4</td>
<td>10-20, 1150</td>
</tr>
<tr>
<td>SPOT-4</td>
<td>HRV, VI</td>
<td>5, 4</td>
<td>10-20, 1150</td>
</tr>
<tr>
<td>RESURS-01-3</td>
<td>MSU-KV</td>
<td>5</td>
<td>170-600</td>
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<tr>
<td>IRS-1B</td>
<td>LISS, PAN</td>
<td>4, 1</td>
<td>36-72, 5.8</td>
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<tr>
<td>IRS-1C, -1D</td>
<td>LISS, PAN</td>
<td>4, 1</td>
<td>23-70, 1150</td>
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<td>IRS-P4 (Oceansat)</td>
<td>OCM</td>
<td>8</td>
<td>560</td>
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<td>JERS-1</td>
<td>VNIR, SWIR, SAR</td>
<td>8, 1</td>
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<tr>
<td>Almaz</td>
<td>SAR</td>
<td>3</td>
<td>4-40</td>
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<tr>
<td>Radarsat</td>
<td>SAR</td>
<td>1</td>
<td>9-100</td>
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<td>ERS-1,-2</td>
<td>AMI (SAR), ATSR</td>
<td>1, 4</td>
<td>26, 1000</td>
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<tr>
<td>Space Imaging</td>
<td>IKONOS-2</td>
<td>5</td>
<td>1-4</td>
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<td>NOAA-15</td>
<td>AVHRR</td>
<td>5</td>
<td>1100</td>
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<td>NOAA-14</td>
<td>AVHRR</td>
<td>5</td>
<td>1100</td>
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<td>NOAA-L</td>
<td>AVHRR</td>
<td>5</td>
<td>1100</td>
</tr>
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<td>Orbview-2 (Seastar)</td>
<td>SeaWiFS</td>
<td>8</td>
<td>1130</td>
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<tr>
<td>CBERS-1</td>
<td>CCD, IRMSS, WFI</td>
<td>5, 4, 2</td>
<td>20, 80-160, 260</td>
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<tr>
<td>Terra (EOS AM-1)</td>
<td>ASTER, MODIS, MISR</td>
<td>14, 36, 4</td>
<td>15, 30, 90, 250, 500, 1000, 275</td>
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<tr>
<td><strong>Proposed satellite (launch window 2000-2007)</strong></td>
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<td>Earthwatch</td>
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<td>Orbview-3</td>
<td>Orbitview</td>
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<td>1-4</td>
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<td>Pan</td>
<td>1</td>
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<td>LISS, AWiFs</td>
<td>7, 3</td>
<td>6-23.5, 80</td>
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<td>SPOT 5</td>
<td>HRV, VI</td>
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<td>5-1150</td>
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<tr>
<td>KVR-100</td>
<td>Camera</td>
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<td>1.5</td>
</tr>
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<td>EO-1</td>
<td>Hyperion</td>
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<td>1</td>
</tr>
<tr>
<td>CBERS-2</td>
<td>CCD, IRMSS, WFI</td>
<td>5, 4, 2</td>
<td>20, 80-160, 260</td>
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<td>Resource21</td>
<td>A, B, C, D</td>
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<td>20</td>
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<td>GLI</td>
<td>36</td>
<td>250-1000</td>
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<td>Kompasat</td>
<td>CCD</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>ARIES</td>
<td>ARIES-1</td>
<td>97</td>
<td>10-30</td>
</tr>
</tbody>
</table>
2.2.2 Remote Sensing for Aboveground Biomass Estimation

Remotely sensed data are understood here as the data generated by sensors from a platform not directly touching or in close proximity to the forest biomass. Therefore, these data comprise images sensed from both aircraft and satellites. Remote-sensing imagery can be extremely useful, particularly where validated or verified with ground measurements and observations (i.e. “ground truth”). Remote-sensing images can be used in the estimation of aboveground biomass in at least three ways (FAO document, 2000)

- Classification of vegetation cover and generation of a vegetation type map. This partitions the spatial variability of vegetation into relatively uniform zones or vegetation classes. These can be very useful in the identification of groups of species and in the spatial interpolation and extrapolation of biomass estimates.
- Indirect estimation of biomass through some form of quantitative relationship (e.g. regression equations) between band ratio indices (NDVI, GVI, etc.) or other measures such as direct radiance values per pixel or

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Sensor Type</th>
<th>Resolution</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALOS</td>
<td>VSAR</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Envisat-1</td>
<td>ASAR</td>
<td>1</td>
<td>30,150</td>
</tr>
<tr>
<td>Radarsat-2</td>
<td>SAR</td>
<td>1</td>
<td>6.25-500</td>
</tr>
<tr>
<td>LightSAR</td>
<td>SAR</td>
<td>4</td>
<td>3-100</td>
</tr>
<tr>
<td>XSTAR</td>
<td>XSTAR</td>
<td>10+</td>
<td>20</td>
</tr>
<tr>
<td>NEMO (HRST)</td>
<td>AVIRIS</td>
<td>211</td>
<td>5-30</td>
</tr>
<tr>
<td>EROS-A1,-A2</td>
<td>Pan</td>
<td>1</td>
<td>1.5</td>
</tr>
<tr>
<td>EROS-B1</td>
<td>Pan</td>
<td>1</td>
<td>0.82</td>
</tr>
<tr>
<td>Aqua(EOS PM-1)</td>
<td>MODIS</td>
<td>36</td>
<td>250-1000</td>
</tr>
<tr>
<td>Resource21</td>
<td>CIRRUS</td>
<td>6</td>
<td>10-100</td>
</tr>
<tr>
<td>M11</td>
<td>MTI</td>
<td>15</td>
<td>5</td>
</tr>
<tr>
<td>NOAA-N</td>
<td>AVHRR</td>
<td>5</td>
<td>1100</td>
</tr>
</tbody>
</table>

digital numbers per pixel, with direct measures of biomass or with parameters related directly to biomass, e.g. leaf area index (LAI).

- Partitioning the spatial variability of vegetation cover into relatively uniform zones or classes, which can be used as a sampling framework for the location of ground observations and measurements.

### 2.2.3 Different Satellite Images in Biomass and C-Stock Estimation

Landsat TM satellite image was used for regional biomass mapping in Madhav National Park-India (Ravan and Roys, 1996). In estimating the biomass, the ground based method was applied. It means that for estimating total above ground biomass (dry weight) natural ecosystem was divided into three components: trees, shrubs and grasses. Ground sampling was carried out by lying sample plots in homogenous vegetation strata. The quantitative measurements of plant parameters in these plots include girth at breast height (for trees) and height of individual plant. The result indicates that there is a significant relationship with spectral responses. These relationships have seasonal dependency in varying phonological conditions. The relationships are strongest in visible bands and middle infrared bands. However, spectral biomass models developed using middle infrared bands would be more reliable as compared to the visible bands as the later spectral regions are less sensitive to atmospheric changes. It was observed that brightness and wetness parameters show very strong relationship with the biomass values. Multiple regression equations using brightness and wetness isolates have been used to predict biomass values. The model used has correlation coefficient of 0.77. Percent error between observed and predicted biomass was 10.5%. The biomass estimated for the entire national park using stratified and...
spectral response modeling approaches were compared and showed similarity with the difference of only 4.69%. The result indicates that satellite remote sensing data provide capability of biomass estimation (Ravan and Roys, 1996).

2.2.4 Remote Sensing Estimation of LAI

Leaf Area Index (LAI) is ratio of the total area of all leaves on a plant to the area of ground covered by the plant (m$^2$/m$^2$). LAI is defined as one sided green area per unit ground area in broadleaf canopies and as projected needle leaf area in coniferous canopies. LAI provides a simple measure of plant canopy density. LAI varies from less than 1 in desert to greater than 10 over tropical rain forest. Therefore, changes in LAI can also be indicative of land cover change (Nemani et al., 1996).

LAI describes a fundamental property of the plant canopy in its interaction with the atmosphere. It is an important structural parameter for quantifying the energy and mass exchange characteristic of terrestrial ecosystem such as photosynthesis, respiration, carbon, and nutrient cycle, and rainfall interception (Gong et al. 2003).

In some remote sensing studies, LAI is expressed as a one-sided ration of leaf area to projected ground area; in others, all sided LAI is measured. LAI is an important structural attribute of forest ecosystem because of its potential to be a measure of energy, gas and water exchanges. For example, physiological processes such as photosynthesis, transpiration and evapo-transpiration are functions of LAI (Pierce and Running 1988). Accordingly, LAI and forest cover type are the two critical inputs available from remote sensing that are required to run ecological process models to estimate growth and productivity across the
LAI may be estimated at a variety of scales and with many different instrument and techniques (Chen and Cihlar, 1995). In the field, LAI can be estimated using litterfall sampling, sapwood allometric and light interception observation and all of labor-intensive and impractical for larger stands and landscapes (Smith et al., 1991; Fassnacht et al., 1994).

Remote sensing estimation of LAI is based on the knowledge that green leaves interact selectively with solar radiation (Jasinski, 1996). Much of the near-infrared energy is reflected by foliage (Knipling, 1970; Gausman, 1977); much of the visible energy (dominated in the red portion of the spectrum) is absorbed by photosynthesis pigments (Waring et al., 1995). Vegetation indices such as NDVI or the simple ration (SR) can be used to capture the way in which red and near-IR reflectance differ in single measure. The common approach of LAI estimation is empirical and semi-empirical modeling; the same approach discussed above, involving correlation of spectral indices with field estimates and the extension of such estimates over large areas with regression (Curran et al., 1992; Peddle et al., 1999; Wulder et al., 1996) or canopy reflectance model (Huemmrich and Goward, 1997).

2.2.5 Vegetation Indices

A vegetation index is a quantitative measure used to measure biomass or vegetative vigor, usually formed from combinations of several spectral bands, whose values are added, divided, or multiplied in order to yield a single value that indicates the amount or vigor of vegetation. The simplest form of vegetation index is a ratio between near infrared and red reflectance. For healthy living vegetation,
this ratio will be high due to the inverse relationship between vegetation brightness in the red and infrared regions of the spectrum.

A vegetation index (VI) was introduced as a simple remote sensing tool for over 25 years. Vegetation indices have been used for many years of increasing importance in the field of remote sensing. VI was a number that is generated by some combinations of remote sensing band and may have some relationship to the amount of vegetation in a given image pixel. Remote sensing devices operated in the green, red and near infrared regions of the electromagnetic spectrum, they act as sensitive discriminators of variations in radiation output that measure both absorption and reflectance effects associated with vegetation.

There are more than 20 vegetation indices in use are summarized in Table 2.4. Many are functionally equivalent (redundant) in information content (Perry and Lautenschlager, 1984), while some provide unique biophysical information (Qi et al., 1995). It is useful to review the historical development of the main indices and provide information about recent advances in index development.

Cohen (1991) suggests that the first true vegetation index was the simple ratio (SR), which is the near-infrared (NIR) to red reflectance ratio described in Birth and McVey (1968)

$$SR = \frac{NIR}{Red}$$

Rouse et al., (1974) developed what is now called the generic Normalized Difference Vegetation Index (NDVI).
Table 2.4 Selected Remote Sensing Vegetation Index (Jensen 2000).

<table>
<thead>
<tr>
<th>Vegetation Index</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Ratio (SR)</td>
<td>( SR = \frac{NIR}{RED} )</td>
</tr>
<tr>
<td>Normalized Difference Vegetation Index (NDVI)</td>
<td>( NDVI = \frac{NIR - red}{NIR + red} )</td>
</tr>
<tr>
<td>Infrared Index (II)</td>
<td>( II = \frac{NIR_{tm4} - MidIR_{tm5}}{NIR_{tm4} + MidIR_{tm5}} )</td>
</tr>
<tr>
<td>Perpendicular Vegetation Index</td>
<td>( PVI = \sqrt{(0.355_{nm34} - 0.149_{nm32})^2 + (0.355_{nm32} - 0.852_{nm42})^2} )</td>
</tr>
<tr>
<td>Greenness Above Bare Soil (GRABS)</td>
<td>( GRABS = G - 0.09178B + 5.58959 )</td>
</tr>
<tr>
<td>Moisture Stress Index (MSI)</td>
<td>( MSI = \frac{MidIR_{TM5}}{NIR_{TM4}} )</td>
</tr>
<tr>
<td>Leaf Specific Water Content Index (LWCI)</td>
<td>( LWCI = \frac{-\log[1 - (NIR_{TM4} - MidIR_{TM5})]}{-\log[1 - NIR_{TM4} - MidIR_{TM5}]} )</td>
</tr>
<tr>
<td>MidIR Index</td>
<td>( MidIR = \frac{MidIR_{TM5}}{NIR_{TM7}} )</td>
</tr>
<tr>
<td>Soil Adjusted Vegetation Index (SAVI) and Modified SAVI (MSAVI)</td>
<td>( SAVI = \frac{(1 + L)(NIR - red)}{NIR + red + L} )</td>
</tr>
<tr>
<td>Atmospheric Resistance Vegetation Index (ARVI)</td>
<td>( ARVI = \left(\frac{p_{nir} - p_{rb}}{p_{nir} + p_{rb}}\right) )</td>
</tr>
<tr>
<td>Soil and Atmospheric Resistance Vegetation Index (SARVI)</td>
<td>( SARVI = \frac{p_{nir} - p_{rb}}{p_{nir} + p_{rb} + L} )</td>
</tr>
<tr>
<td>Enhanced Vegetation Index (EVI)</td>
<td>( EVI = \frac{p_{nir} - p_{red}}{p_{nir} + C_1p_{blue} - C_2p_{blue} + L}(1 + L) )</td>
</tr>
</tbody>
</table>

### 2.2.5.1 Simple Ratio (SR)

Cohen (1991) suggest that the first true vegetation index was the Simple Ratio (SR), which is the near-infrared (NIR) to red reflectance ratio described in Birth and McVey (1968); in Jensen (2000)

\[ SR = \frac{RED}{NIR} \]
2.2.5.2 Normalized Difference Vegetation Index (NDVI)

NDVI (Normalized Difference Vegetation Index) is one of the ratio indices that respond to changes in amount of green biomass, chlorophyll content and canopy water stress. The healthy and dense vegetation show a large NDVI. Areas covered with clouds, water and snow yield negative index value while areas covered with rock and bare soil result in vegetation indices near zero.

The pigment in plant leaves, chlorophyll strongly absorbs visible light (from 0.4 to 0.7 µm) for use in the photosynthesis. The cell structure, on the other hand, strongly reflects near infrared light (from 0.7 to 1.1 µm). The more leaves a plant has, the more these wavelengths of light are affected, respectively.

By comparing visible and infrared light, scientist measures the relative amount of vegetation. Healthy and dense vegetation absorbs most of the visible light that hits it. Unhealthy and sparse vegetation reflects more visible light and less near infrared. Mathematically, NDVI is written as:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

The actual difference between the reflected sunlight from the red part of the spectrum and the reflected energy in the near infrared gives a qualitative measure for photosynthesis activity. NDVI value range from minus one (-1.0) to plus one (+1.0) and are unitless (Wunderle et al, 2003).

NDVI is a good indicator of the ability for vegetation to absorb photosynthetically active radiation has been widely used by researcher to estimate green biomass, LAI and patterns of productivity. The main advantages of the use of the NDVI for monitoring vegetation are the simplicity of calculation, the high degree of correlation of the NDVI with a variety of vegetation parameters and the
extensive area coverage and high temporal frequency of remote sensing data (Hess T. et al, 1996).

Environmental factors such as soil geomorphology and vegetation all influence NDVI values should be taken into account. NDVI can be effective in predicting surface properties when vegetation canopy is not too dense or too sparse. If a canopy is too sparse, background signal (e.g. soil) can change NDVI significantly. Depending on the vegetation coverage, dark soil enhances the NDVI (Wunderle et al, 2003). If the canopy too dense, NDVI saturates because red reflectance does not change much, but NIR reflectance still increase when the canopy become denser.

A few studies have attempted to predict forest biomass using the relationships between reflectance and crown closure, crown size, and species. In Japan, Lee and Nakane (1997) estimated biomass with a variety of vegetation indices obtained from Landsat TM Imagery in predominantly deciduous stands (comprised of Quercus serrata, Catanea crenata and Carpinus laxiflora), pine (Pinus densiflora) forests, and Japanese cedar (Cryptomeria japonica) plantation. The NDVI was best in predicting biomass in the pine stands (R value was 0.85). In the deciduous and cedar plantations, the difference between band 5 and 7 (called the DVI) was the best predictor (R value=-0.83 for cedar, and +0.80 for deciduous stands) (Table 2.5).

Table 2.5 The relationship between Landsat TM-Based DVI (Difference between bands 5 and 7) and biomass in 33 stands of deciduous and cedar plantation in Japan.

<table>
<thead>
<tr>
<th>Stand Type</th>
<th>R Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cedar</td>
<td>-0.83</td>
</tr>
<tr>
<td>Deciduous</td>
<td>+0.80</td>
</tr>
</tbody>
</table>

Source: Adapted from Lee and Nakane (1997)
The sign of the relationship between biomass and DVI changed in the cedar plantations compared to the deciduous stands. The cedar plantation was comprised of stands with the relatively similar age classes. Trees were a uniform diameter and canopy height. The spectral response was more scattered due to the sharp, triangular cedar crown. The DVI was thought to be more sensitive to vegetation density than to leaf moisture content and color. The changes in the relationship among the species were attributed to the influences of different shadowing and leaf biomass.

Biomass distribution in forest ecosystem is a function of vegetation type, its structure and site condition. Ground based sampling in functional homogenous vegetation categories is an approach which has found acceptability in the recent past (Shute and West 1982)

The NDVI has been shown to be useful in estimating vegetation properties, many important external and internal influence restrict its global utility.

2.3 Empirical Modeling

Empirical models are based on statistical analysis of observed data, and these are usually applicable only to the same conditions under which the observations were made. An empirical model is based only on data and is used to predict but not to explain the process of system. An empirical model consists of a function that captures the trend of the data. Data are essential for an empirical model.

Sometimes with a derived model, it might be difficult or impossible to differentiate or integrate a function to perform further analysis. Empirical
modeling (EM) offered both a broad foundational perspective on computing and a novel practical approach to modeling. Central to the EM perspective was an emphasis on the power of the computer to represent state in particular, state that was easily interpretable. Adopting a broad concept of what constituted a computer any reliable, interpretable, state changing device led to a view in which the context for computing (e.g. other devices and users) was significant as the computer itself.

Empirical model application was used to estimate biomass and carbon stock of oil palm (Htut, 2004). Empirical model using correlation analysis was very useful to examine the validation of field data to estimate LAI by using various remote sensing data and various crops. In addition, ground truth data was essential to estimate LAI based on NDVI. Fieldwork should still be undertaken, to get specific information that couldn’t be derived from the images.