CHAPTER 7

GENERAL DISCUSSION

The estimation of Biomass and Net Primary Productivity (NPP) is a key parameter in Carbon dynamics studies. The NPP studies are carried out at various levels, and a variety of Remote sensing data is now available for different levels of studies. At global level NOAA/AVHRR, SPOT-4 vegetation and MODIS data are providing promising results. IRS WiFS, AWiFS and OCM data provide valuable tool for National level studies. For regional level studies IRS AWiFS and IRS LISS III provide valuable data where as for local spatial scale IRS LISS-IV and fused products of IRS LISS-III and PAN are much suited.

Primarily the NPP can be estimated through three basic methods:

- Through assessment of total biomass produced during a growing season (Chaturvedi and Singh, 1987, Rawat and Singh, 1988)
- A net gas exchange by plants, normally the difference between GPP and autotrophic respiration
- Through quantification of growth limiting factors like climate, CO$_2$ concentration, Soil fertility and total solar radiation.

A number of attempts have been made for modeling global terrestrial NPP. Lieth (1995) and Rosenzweig (1968) estimated NPP using climatic data. Since than a number of ecosystem process based models have
been developed that link climate, soil properties and biome specific characteristics to responses in biogeochemical processes of vegetation (Haxeltine and Prentice 1996; Knorr & Heimann 1996; kohlmair et al 1997; Melillo et al 1993; Woodword et al 1995). A few models have been designed to compute global NPP directly from remote sensing data (Field et al 1995; Prince and Goward, 1995; Ruimy et al 1996) The NPP models range in complexity from fairly simple regression between key climatic variables and one or several biospheric gas fluxes, to quasi-mechanistic models that attempt to simulate the biophysical and ecophysiological processes occurring at plant level. Each approach is based on simplifying assumption about how vegetation may respond to changes in various environmental parameters (Churkina & Running 1998).

The models available for NPP estimations can be broadly categorized as:

1. Leaf area based
2. Climate based
3. Radiation based
4. Hierarchical aggregation based
Leaf Area Based Approach:

The remote sensing data is greatly influenced by the leaf area index (LAI). The LAI is the surface area of leaves per unit area of ground. The normalized difference vegetation index (NDVI) have been found to have a significant relationship with LAI. Since foliage is the site of the photosynthesis and leaf area has direct influence on NPP, it is possible to compute NPP by establishing relationship between LAI and NPP. However, this approach leads to uncertainties while dealing with an area having variety of vegetation types. Each vegetation type has a varying efficiency to trap and convert light energy in chemical energy. In such cases a simple relationship often leads to crude estimates. Some of the LAI based models, for example “Canopy Photosynthesis Models” (Running S. W., and J.C. Coughlan, 1988) simulate growth and canopy development together based on climate and other environmental factors. All these models use LAI as the basis of estimation of light absorption. To estimate NPP, LAI models LAI models either explicity allocate carbon to a specific reservoir to growing leaves, or they optimize LAI according to water or carbon balance constraints (Boneau et al 1999). The BIOMZE-3 and KGBM (Kergoat Global Biospheric Model) (Kergoat, 1998), both determine potential LAI from available water (and carbon for BIOME-3). Te CARAIB model ( Cabon assimilation in biosphere model) (Nemry et al 1996) uses a priory information on the LAI of different pant functional types based on Potential Evapo-transpiration (PET), and optimize LAI
monthly. The FBM (Frankfurt Biospheric Model) (Kindermann et al 1993; Ludeke et al 1994; Kohlmaier et al 1997), PLAI model (Postdam Land atmosphere Interaction Model) (Plochi & Cramer, 1995), SILVAN model (Simulating Land Vegetation and NPP Model) (Kaduk & Heimann, 1996) and HYBRID model (Friend et al 1997) develop LAI as a result of allocation and carbon balance. These four models start with an LAI at or close to zero and simulate the growth of plants with increasing LAI over multiple years.

**Climate based Models**

Climate based models assume that NPP is limited by climatic variables. The famous Miami model (Lieth, 1975) computes independent estimates for NPP using precipitation and temperature, and, minimum of these two if considered as the estimated NPP. In this model the soil, vegetation type, solar radiation and other factors limiting NPP were not considered.

Water balance, which integrates precipitation input, oil water storage and evapotranspiration has been advocated to have a dominant control over NPP (Grier and Running, 1977; Golz, 1982). Stephenson (1990) exhibited high correlation between North American plant formations and water balance parameters. Churkina et al (1999) based on analysis of earlier studies strongly suggested that water balance in the primary driver of variation in NPP.
Potential and actual evapotranspiration (PET and AET) are the most significant water balance parameters. PET is the amount of evapotranspiration that could occur, if the soil of a large area having typical vegetation of surroundings, was kept continuously wet (Rosenzweig, 1968). AET is the amount of water actually entering the atmosphere from soil and vegetation (Rosenzweig, 1968). Global NPP models used six different methods for calculation of PET. These area Penman-Monteith method (Monteith, 1973), Penman (1948) method, Thornwaite (1944, 1948) method, Priestley-Taylor method (Priestley and Taylor, 1972), Jarvis-McNaughton method (Jarvis and McNaughton, 1986) and Jensen-Haise method (Jensen and Haise, 1963). The Penman-Monteith and Priestley – Taylor methods, depend on climatic variables such as temperature and radiation as well as on plant cover type. On the other hand, Panman, Jensen-Haise, Thornthwaite and Jarvis-McNaughton methods use climatic parameters only. Calculation of evapotranspiration is based on radiation and temperature in the Jensen-Haise and Jenson-McNaughton methods, but only on temperature in the Thornthwaite method. The Penman and Penman-Monteith methods also require air humidity data (CHurkina et al 1999).

A few models like TURK terrestrial Uptake and Release of Carbon (Ruimy et al 1996) and GLO-PEM (Global Production Efficiency Model) (Prince, 1991; Prince & Goward, 1995) inferred water availability limitation on NPP entirely from satellite data. Water stress limits were reported by
Garcia et al (1988) using NDVI, through a hand held radiometer. Subsequently, Nemani and Running (1989) and Nemani et al (1993) estimated surface moisture status through satellite data using a relationship between NDVI and surface temperature ($T_{\text{surf}}$). For moist environment $T_{\text{surf}}$ provided no distinction between soil and leaves. In dry conditions, green foliage increased NDVI, but decreased $T_{\text{surf}}$, because of the increasing amount of evaporated water. The TURC model incorporated water limitation on NPP solely through a light interception efficiency coefficient derived from NDVI data. The GLO-PEM model included water restrictions on NPP through a moisture index dependent on NDVI/ $T_{\text{surf}}$

The periodicity of data (i.e., time interval) has a significant bearing on computation of water balance, which ultimately affects the NPP estimates. The monthly average rainfall data provide the total input of rain water. However, this does not provide the information on rain frequency and intensity which varies from region to region. Further, the partitioning of rainfall including canopy interception, infiltration, run-off and snow melt evaporation is also limited through monthly data. Plant may experience water stress and re-hydration, both in one month but these dynamics cannot be shown using monthly time interval. Thus, the use of daily time step has been advocated to improve the estimates of water related variables.
To compare estimates of annual NPP in relation to water availability, Churkina et al (1999) introduced a simple water balance coefficient which differentiates sites with surplus water from the sites with deficient available water. The coefficient can be used with all models regardless of there individual hydrological computations. Churkina and Running (1998) plotted NPP estimated by BIOME-BGC model in climate space represented by temperature and water availability to examine relationship between NPP and climate control.

**Radiation based Models**

These models are based on the assumption that the productivity of terrestrial biosphere depends on the ability of terrestrial vegetation to capture and use solar radiation (Bondeau et al 1999). Although light use is influenced by other environmental factors such as climate control and soil fertility, the capture of solar radiation solely depend on the structural character of vegetation. Terrestrial biosphere model use different approaches to represent vegetation structure and its variation across the globe.

Radiation based models are also teamed as production efficiency models (PEM) as they are based on the efficiency of the terrestrial system to convert solar radiation to chemical energy. These models use capital NDVI data from Satellites to determine fraction of photo synthetically active radiation (FPAR). In this approach, the influence of
vegetation canopy structure and its phenology on seasonal NPP are largely represented by seasonal variation in FPAR. However, different PEMs use different algorithms to calculate FPAR from NDVI data sets. The FPAR for the production efficiency models is based on monthly LAI using Beer-Lambert Law:

\[ \text{FPAR} = 0.95 \times (1 - \exp(-k \times \text{LAI})) \]

Where, \( k \) is the light extinction coefficient, which varies around 0.5 for green vegetation.

Monteith (1972, 1977) suggested that NPP under non-stressed conditions is linearly related to the amount of photosynthetically active radiation (PAR) that is absorbed by the green foliage (APAR). Kumar and Monteith (1981) showed how fraction of PAR absorbed relates to the ratio of red reflectance (R) to near-infrared (NIR) reflectance. Asrar et al (1984) subsequently related the NDVI to the fraction of PAR absorbed, which suggests that NDVI may be used to estimate NPP at global scales by (Hunt Jr., 1994):

\[ \text{NPP} = \varepsilon \sum (\text{APAR}) = \varepsilon \sum (\text{NDVI} \times \text{PAR}) \]

Where, \( \sum (\text{APAR}) \) is annual sum of APAR and \( \varepsilon \) is the PAR conversion efficiency. Jarvis and Leverenz (1984) presented a simple model of \( \varepsilon \), which is used to separate the factors controlling NPP:

\[ \varepsilon = \varepsilon_{\text{max}} f Y_m Y_g d \]
Where, $\varepsilon_{\text{max}}$ is maximum PAR conversion efficiency (gMJ$^{-1}$). F is the fraction when photosynthesis is not reduced by climatic factors (such as drought, high vapour pressure deficit or cold temperature), $Y_m$ is the maintenance respiration, $Y_g$ is the growth respiration and d is the dry matter not lost by death, turnover and herbivory. Based on quantum yield of photosynthesis, Jarvia and Leverenge (1984) and Russel et al (1989) calculated that $E_{\text{max}}$ should be about 5/4 g MJ$^{-1}$ for plants with C$_3$ photosynthetic pathway. The $Y_m$ and $Y_g$ are defined as:

$$Y_g = 1 - R_g / P$$

$$Y_m = 1 - P_m / P Y_g$$

Where, $P$ is the amount of net photosynthesis (g m$^{-2}$ yr$^{-1}$), $R_m$ is the amount of non-foliar maintenance respiration (g m$^{-2}$ yr$^{-1}$) and $R_g$ is the growth respiration (g m$^{-2}$ yr$^{-1}$). As forests gain age and accumulate dry mater $Y_m$ should decrease because of increased $R_m$, thereby decreasing $\varepsilon$. (Jarvis & Leverenge 1984; Hunt and Running 1992; Hunt Jr., 1994).

**Hierarchical Aggregation Model:**

Most of the models describes above use indirect measurement of net primary productivity. It is often difficult to validate the output of these models due to lack of field data on NPP. The multistage sampling procedure allows translating the field measure NPP to regional levels at special seal. Example of this approach is given in Singh (1995) and
Tiwari (1995). The forest Biomass forms a principal variable for the analysis. For forest biomass mapping, a method was developed by Tiwari and Singh (1984) using a real photograph, which was extended to satellite Remote sensing by Tiwari (1994). The estimation of biomass over larger areas needed generalized biomass estimation equations based on allometry. Some of the workers (Brown and Lugo 1982) used timbre volume estimation equations, which provided volume of commercial timbre alongwith an expansion factor to compute total tree biomass. However, such an approach leads to major uncertainty in biomass estimates. On the other hand, harvesting of trees for generation of biomass equation is impossible due to current forest protection legislation. A non-harvesting modeling approach developed by Tiwari (1992) is a viable alternative for generation of biomass estimation equations for any number of species, with an acceptable level of accuracy.

The present study is focused on the spectral modeling forest biomass and Net Primary Productivity in Doon valley using biophysical parameters viz., forest type, crown cover, tree height, girth, solar radiation, elevation, slope, aspect and the spectral values recorded by the remote sensing sensor. The study is carried out by the preparation of Land use and vegetation map, Mapping of biophysical parameters, Spectral modeling of total above ground biomass map and Spectral modeling of Net Primary Productivity.
Table 3.3 represents various land use and vegetation types in Doon valley. Major five forest types (Sal (old growth), Sal coppice, Sal mixed, Oak, Pine and Acacia) have been identified. Forests are found spreading over 82522.59 ha area (45.19% of total geographical area). Non-forest includes the scrub, agriculture, fallow, tea garden, and plantation in addition with riverbed, water body and settlements. 54.8 % of the total geographical area is accounted for non-forest area. In the total forest area, Sal mixed forests were the most dominated forest of the area, occupying 51.40 % of the total forested land and 23.23 % of the total geographic area followed by Sal coppice and Sal (old growth) forests. In the areas of Central Himalaya, Tiwari and Singh, 1987 analysed the vegetation pattern. According to their analysis, Shorea robusta foresr dominated in the area followed by Pinus roxburghii. Shores robusta in Central Himalaya is confined to shales and sand stones of Siwalik Hills (Tiwari, 1983). The present study area falls in the Siwalik hills.

Within the various forest type classes, four crown cover classes (< 20 %, 21 – 40 %, 41 – 70 %, > 70 %) were recorded, out of which maximum area is occupied by 41 – 70 % crown cover class (56.24 %) followed by 21 – 40 % crown cover class and > 70 % crown cover class (9.21 %). The crown class < 20 % occupies least forested area (7.09 %). The study area has altitudinal variation of 300 m to 2300 m. Out of these, Sal species (Shorea robusta) forests were confined to lower elevation zones, i.e. up to 1200 meters of elevation. Pinus roxburghii forest has
shown dominance up to an altitude up to 1800 meters. Oak forests are found in the elevation greater than 1500 meters. Between 1600 to 1900 m altitude, the presence of Oak and Pine forest is mainly determined by soil texture, which contributes to variation in water holding capacity and available moisture. Most of the natural forests exhibited their maximum proportion under North and North-Eastern aspects. Sal dominated forests are confined to North and North-East aspects. Oak forests are also present in the Northern slopes. Northern slopes are supposed to bear higher moisture which makes it much suitable for Oak forests. Pine forests are confined to southern slopes. The climate of the area is greatly influenced by slope, aspect and Digital Elevation Model (DEM) (Figure 4.1). The slope and aspect maps were generated from DEM. The output slope map indicated slope ranges from 0 to 90° which were re-grouped in to 8 classes (Figure 4.2 & 4.3, Table 4.2 & 4.3.). The land use and vegetation map is overlaid on slope, aspect and DEM to study the spatial variation of different land use classes in different slope, aspect and altitudinal ranges. 74.74 % of the total geographical area is confined to < 10 degree slope.

In the present study, the total above ground biomass was estimated through crown cover based approach and spectral model approach. In the crown cover based approach, the total above ground biomass in the entire study area is 1781.9 x 104 tons. Among different forest types, maximum above ground forest biomass (1005.77 x 104 tons) is found in Sal mixed forests followed by Sal (old growth) forests (339.6 x 104 tons).
and Sal coppice forests (304.9 x 104 tons). Oak forest has a total above ground biomass of 56.8 x 104 tons. The total above ground biomass of Pine forest is comparatively less in the study area and is found to be 28 x 104 tons. The total above ground biomass occupied by Acacia forest is 46.8 x 104 tons. The mean total above ground biomass ranges from 43.65 t ha⁻¹ (Sal coppice with < 20 % crown cover) to 371 t ha⁻¹ (oak forests with > 70 % crown cover). In the Sal forests, the highest mean biomass is found in > 70 % crown cover such as Sal (old growth) has 312.64 t ha⁻¹, Sal coppice has 309.93 t ha⁻¹ and Sal mixed forests have 332.03 t ha⁻¹. Oak forests have shown the highest mean biomass in all the crown cover classes such as 158.27 t ha⁻¹ in < 20 %, 208.11 t ha⁻¹ in 20 – 40 %, 289.59 t ha⁻¹ in 40 – 70 % and 371.13 t ha⁻¹ in > 70 % crown cover classes. Pine forests have shown less mean biomass such as 70.52 t ha⁻¹ in < 20 % crown cover class, 113.23 t ha⁻¹ in 20 – 40 % crown cover class and 151.17 t ha⁻¹ in 40 – 70 % crown cover class. In Acacia forests, the mean biomass is 182 t ha⁻¹. The biomass density of Sal mixed forests is 237.12 t ha⁻¹, which is higher than newly growth Sal forests. Similarly Oak forests of Doon valley have greater biomass density, 276.82 t ha⁻¹ than other forest types. Chir pine forest has shown less biomass density, 98.68 t ha⁻¹.

A spectral relationship was established between the total above ground biomass estimated from the field and the spectral values from all the four bands of IRS-P6 AWiFS data. The spectral relationship has
shown high to medium correlation. In all the cases best $R^2$ values between total above ground biomass and spectral values were obtained while using all the four bands of AWiFS. The $R^2$ value ranges from 0.73 to 0.92. However, the $R^2$ value was lowest in case of pine forest (0.73). The Sal old growth forest indicated best $R^2$ value (0.92) for this relationship. All the relationship indicates high intercept values, which shows strong negative relationship of biomass with some of the spectral bands. The biomass was mapped in to discrete classes of 80 t ha$^{-1}$ intervals such as < 80, 80–160, 161-240, 241-320 and > 320 t ha$^{-1}$. Using this spectral model approach, the Sal mixed forest has shown a maximum of total above ground biomass of 1011.3 x $10^4$ tons followed by Sal (old growth) forest (336.3 x $10^4$ tons) and Sal coppice forest (305 x $10^4$ tons). Oak forest has shown a total above ground biomass of 56.5 x $10^4$ tons and Pine forest has shown 28.4 x $10^4$ tons. Incase of biomass density, Oak forest has shown a maximum biomass density of 275.54 t ha$^{-1}$ followed by Sal mixed forest (238 t ha$^{-1}$) and Sal (old growth) forest (232.12 t ha$^{-1}$). Sal coppice has shown a biomass density of 168.15 t ha$^{-1}$ and Pine forest has a biomass density of 99.82 t ha$^{-1}$. Acacia forest has shown a biomass density of 182 t ha$^{-1}$.

The study has been validated by comparing the total above ground biomass values from the spectral model approach and those from the crown cover based approaches. Both the data sets exhibited a close
agreement with $R^2$ value 0.9365 gives confidence to the estimates of the present study.

The relationship between the biomass allocation in different tree components such as bole, branch, twigs and foliage and mean annual solar radiation in forest type wise is presented in the figures 7.1 to 7.5. In the oak forests, except for component foliage, biomass allocation in bole, branch and twigs showed good relationships with mean annual solar radiation. The $R^2$ values were found to be 0.94, 0.94, and 0.93 respectively. For foliage, the $R^2$ was found to be 0.42. However, in the case of bole, the biomass allocation decreases with increase of mean annual solar radiation and in the case of branch and twigs, biomass allocation increases with increase in mean annual solar radiation.

For the spectral modeling Net Primary Productivity (NPP), the NPP of the tree layer of the reference sites were calculated as $NPP = \Delta b$ + litter fall + Root mortality Where $NPP = \text{the Net Primary Productivity/hectare/year, } \Delta b = \text{the difference in biomass in the trees during one year period in one hectare. In this study, two approaches were attempted for regional estimation of NPP viz., crown cover based approach and Spectral model approach. In the crown cover approach, a relationship was developed between crown cover of each forest type and the Net Primary Productivity obtained from reference sites and the respective crown cover values were replaced with the Net Primary Productivity values obtained from the above relationship. Among different forest types, the mean NPP}
ranged between 4 t ha\(^{-1}\) yr\(^{-1}\) (Sal coppice forest < 20 \% crown cover) to 17.3 t ha\(^{-1}\) yr\(^{-1}\) (Sal mixed forest > 70 \% crown cover). The total above ground Net Primary Productivity was maximum in Sal mixed forest (43.2 x 10\(^4\) t yr\(^{-1}\)) followed by Sal coppice forest (19.1 x 10\(^4\) t yr\(^{-1}\)). Acacia forest exhibited a total Net Primary Productivity of 1.3 x 10\(^4\) t yr\(^{-1}\). Sal (Old growth) forest has shown a maximum average Net Primary Productivity of 12.1 t ha\(^{-1}\) yr\(^{-1}\) followed by Oak (10.9 t ha\(^{-1}\) yr\(^{-1}\)) and Sal coppice forest (10.5 t ha\(^{-1}\) yr\(^{-1}\)) and Sal mixed forest (10.2 t ha\(^{-1}\) yr\(^{-1}\)). Pine forest has shown an average Net Primary Productivity of 6.8 t ha\(^{-1}\) yr\(^{-1}\). In the spectral model approach, a spectral relationship was established between field measured NPP of the entire Doon valley with spectral values of the four bands of IRS-P6 AWiFS data. The output NPP map were generated with 5 classes (< 2 t ha\(^{-1}\) yr\(^{-1}\), 2-5 t ha\(^{-1}\) yr\(^{-1}\), 5-10 t ha\(^{-1}\) yr\(^{-1}\), 10-15 t ha\(^{-1}\) yr\(^{-1}\) and > 15 t ha\(^{-1}\) yr\(^{-1}\)). The spectral model based estimate indicated a maximum total above ground Net Primary Productivity for Sal mixed forest (42.8 x 10\(^4\) t yr\(^{-1}\)) followed by Sal coppice forest (19.2 x 10\(^4\) t yr\(^{-1}\)). Sal (old growth) forests has shown a total Net Primary Productivity of 17.9 x 10\(^4\) t yr\(^{-1}\). Oak and Pine has a total above ground Net Primary Productivity of 2.2 x 10\(^4\) t yr\(^{-1}\) and 1.8 x 10\(^4\) t yr\(^{-1}\) respectively. The mean Net Primary Productivity for different forest types indicated that Sal (old growth) has shown a maximum average Net Primary Productivity 12.4 t ha\(^{-1}\) yr\(^{-1}\) followed by Oak forest (10.80 t ha\(^{-1}\) yr\(^{-1}\)). The Sal coppice has shown an average Net Primary Productivity of 10.6 t ha\(^{-1}\) yr\(^{-1}\) and Sal mixed has
shown 10.1 t ha\(^{-1}\) yr\(^{-1}\). Pine forest has shown an average Net Primary Productivity of 6.5 t ha\(^{-1}\) yr\(^{-1}\).

The result has been validated by comparing the NPP values of crown cover based approach and spectral model approach. A relationship has been established by plotting the NPP values of 15 reference sites estimated through crown cover based approach against those estimated through spectral model. The relation has shown 98.32 % correspondence, which gives confidence to the present study.

For a total of 25 sites, the total above ground biomass computed in the present study was related to the independent estimate of productivity collected under IGBP program (AKT unpublished). The Sal forest (old growth) exhibited a significant highly correlated relationship between biomass and productivity (Figure 7.6). Productivity appears to increase with increase in biomass up to about 320 t ha\(^{-1}\) where as after this biomass level, a decreasing trend of productivity was observed. On contrary, Sal copice forest exhibited ever increasing trend of productivity (figure 7.7). The reason for this trend is due to the fact that the higher biomass in Sal coppice forest is accounted due to higher density of trees per unit area. The average age of trees is relatively less and these trees have a good potential to accumulate more biomass. On the other hand, the higher biomass in old growth forest is due to larger girth of trees and higher amount of biomass per tree. This results in higher amount of
respiratory loss to maintain the living tissues which ultimately results in a lower level of productivity.

In case of Sal mix forest, there is a slow increase in productivity up to the biomass level of about 210 t ha$^{-1}$. A biomass range of about 200 to 350 t ha$^{-1}$ appears to have a high biomass to productivity ratio. The productivity shows a decreasing trend after 350 t ha$^{-1}$ of the biomass (Figure 7.8). The initial slow increase in productivity in low biomass forest may be the result of disturbance in the forest.

Pine forests exhibited a sharp increase in productivity with increase in biomass up to a total above ground biomass of 150 t ha$^{-1}$. The curve drawn using second order polynomial equation exhibits an $R^2$ of 0.92 (Figure 7.9).

Oak forest exhibited an increasing trend of productivity with increase in biomass. However, visualization of data indicate two different trends in lower biomass ranges (within 50 to 100 t ha$^{-1}$) as marked A in the figure 7.10. The higher slope at this region indicates the presence of dense under growth of grasses which is responsible for higher Net Primary productivity where as the sites showing lower slopes are having spares herbaceous vegetation in understory and are prone to disturbance. The sites marked as B indicate a few out layer sites showing lower productivity because of excessive lopping.
Figure 7.1. Biomass allocation of different tree components of Sal (OG) forests with mean annual solar radiation
Figure 7.2. Biomass allocation of different tree components of Sal coppice forests with mean annual solar radiation
Figure 7.3. Biomass allocation of different tree components of Sal mixed forests with mean annual solar radiation
Figure 7.4. Biomass allocation of different tree components of Oak forests with mean annual solar radiation
Figure 7.5. Biomass allocation of different tree components of Pine forest with mean annual solar radiation
Figure 7.6  Relationship between total above ground biomass (t ha⁻¹) and Net Primary Productivity (t ha⁻¹ yr⁻¹) of Sal (OG) Forest.

Figure 7.7. Relationship between total above ground biomass (t ha⁻¹) and Net Primary Productivity (t ha⁻¹ yr⁻¹) of Sal coppice forest.
Figure 7.8. Relationship between total above ground biomass (t ha\(^{-1}\)) and Net Primary Productivity (t ha\(^{-1}\) yr\(^{-1}\)) of Sal mixed forest.

Figure 7.9. Relationship between total above ground biomass (t ha\(^{-1}\)) and Net Primary Productivity (t ha\(^{-1}\) yr\(^{-1}\)) of Pine forest.
Figure 7.10. Relationship between total above ground biomass (t ha\(^{-1}\)) and Net Primary Productivity (t ha\(^{-1}\) yr\(^{-1}\)) of Oak forest.