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# ABOVE GROUND FOREST BIOMASS DISTRIBUTION IN THE LANDSCAPE OF JORHAT, ASSAM, INDIA

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**Abstract**
This study aims to analyze the spatial and temporal variations in above-ground biomass (AGB) within the Jorhat region from 2001 to 2023. It also highlights the impacts of urbanization, physiographic characteristics, and soil types on AGB variation. In order to accurately assess landscape-level variation of biomass, a combination of field surveys, remote sensing techniques, and modelling approaches are employed in this study. Biomass estimation is difficult over large area using traditional method. The synoptic nature of satellite-based data improves the monitoring of inaccessible areas. Results show approximately 16.6% decrease in AGB, with urban and peripheral areas experiencing the most notable declines due to reduced forest cover. Physiographic analysis reveals low AGB values in marshes (13 t/ha), swamps (14 t/ha), and char lands (25 t/ha). The growth of trees is suppressed seasonal flooding in this physiography. Additionally, AGB follows an increasing trend from North to South, in alignment with the region's elevation profile. Soils also exhibit variations in AGB, with alluvial soils supporting higher biomass compared to other soil types. Key ecological linkages and spatial patterns are highlighted in this study, laying the groundwork for more proactive and comprehensive environmental management. Finally, in a time of fast environmental change, these insights can assist stakeholders and policymakers in creating more evidence-based, flexible solutions to protect ecosystems.

***Keywords:*** above-ground biomass, estimate, land, spatial variation

## 1. Introduction

Land is the most important natural resources on which all activities are based (Sahariah et al., 2015). Land cover refers to the physical characteristics of the earth's surface, captured in the distribution of vegetation, water, soil and other physical features of the land (Rawat and Kumar, 2015). The arrangement of various natural and human-made features within a landscape, such as forests, wetlands, urban zones, and agricultural fields, reveals the underlying ecological processes, habitat connectivity, and biodiversity hotspots (Li et al., 2022). Forest distribution has a landscape-level impact (Wigley and Robert, 1997). Biomass is defined as the total quantity of live and inert or dead organic matter, above and below the ground, expressed in tons per unit area, such as hectare (Wani et al. 2012). Information on above-ground biomass (AGB) is important for forest resource management at local and regional levels for carbon emission reporting. Biomass assessment is important since it helps in knowing the amount of carbon sequestered by a forest since 47.5-50% of forest biomass is carbon (Dixon et al., 1994; Das et al., 2012). It is necessary for a better understanding of deforestation impacts on global warming and environmental degradation (Lu, 2002). It is of utmost importance to protect forests from degradation and sustainable management because it affects the available natural carbon and above ground biomass (Wondem, 2015). According to Brown et.al (1999), the quantity of biomass in a forest determines the potential amount of carbon. Above-ground biomasses (AGB) of trees contain a large fraction of the total forest carbon stock (Das et al., 2021). Carbon capture and storage (CCS) is significant for the reduction of carbon dioxide ($CO_2$) emissions from industrial processes and power generation, helping to mitigate the impacts of climate change. As countries strive to achieve the Sustainable Development Goals (SDGs), CCS plays an essential role in supporting several goals, particularly SDG 13: Climate Action, which focuses on urgent action to combat climate change and its impacts (Roy et al, 2023). Topography and elevation gradients influence moisture availability, temperature variations, and light exposure, which in turn impact species composition and forest growth patterns (Saatchi et al., 2009). Similarly, geomorphological features such as valleys, floodplains, and slopes affect water retention, nutrient cycling, and soil erosion, directly influencing forest productivity. Soil types, with their varying physical and chemical properties, play a vital role in determining nutrient availability and water-holding capacity, key factors for biomass accumulation (Osuri et al., 2014). Moreover, climate variables such as temperature and precipitation govern the broader ecological processes that drive forest growth, resilience, and carbon storage.

For the Jorhat district in Assam, accurate biomass estimations are essential for climate change mitigation efforts (Goswami et al., 2016) and sustainable forest management with increasing population (Shahina et al.,2025). Estimating biomass has become more important in agrarian regions like Jorhat, where rural livelihoods are strongly correlated with natural resources. Because of its varied land cover types, seasonal flooding patterns, and socio-ecological dynamics, the Jorhat district in Assam's Upper Brahmaputra Valley agro-climatic region poses particular difficulties for biomass assessment. In order to create a reliable and locally relevant biomass estimating system that may aid in the Jorhat district's scientific comprehension and policymaking, these issues must be resolved.

This study aims to analyze the spatial distribution of Above-Ground Biomass (AGB) across varied landscapes in the Jorhat area of Assam. It also examines temporal variations in AGB over time. By analyzing spatial and temporal variations in AGB, this research seeks to offer insights into how do spatial and temporal variations in above-ground biomass (AGB) influence forest ecosystems across different landscapes in the Jorhat area of Assam?

## 2. Study area

Jorhat, located in the central part of the Upper Assam valley, lies between the latitudes of 26°20' N to 27°10' N and longitudes of 93°57' E to 94°37' E. Bordered by the Brahmaputra River to the north and the Naga Hills to the south, the region exhibits diverse topography and landscape features. The area is predominantly formed by alluvial sediments deposited by the Brahmaputra River, which has shaped much of the terrain. The elevation of Jorhat ranges from 60 meters to 140 meters above mean sea level (MSL), while the southern and southeastern parts of the district rise into low hill ranges, which are an extension of the Naga Hills. These hills have altitudes ranging from 150 meters to

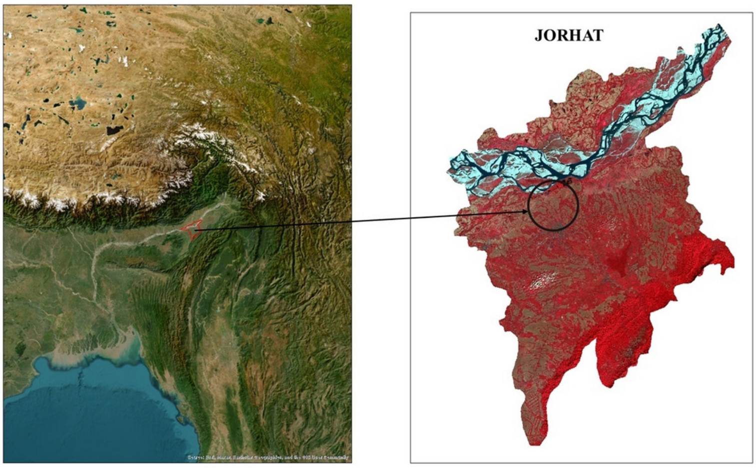


Fig.1. Study area: Jorhat

450 meters above MSL. The hill ranges are characterized by moderately steep to steep slopes and are primarily forested.

Jorhat's varied physiography, with its flat alluvial plains transitioning into hilly terrain, creates diverse ecological zones, from fertile agricultural lands in the lowlands to forested areas in the elevated hills. This geographic diversity, combined with its proximity to the Brahmaputra River, makes Jorhat an important ecological and agricultural region, with landscape patterns significantly influenced by riverine processes and hill slopes.

## 3. Database

I. Diameter at breast height of trees were measured randomly (Chhetri and Fowler, 1996; Magalhaes and Seifert, 2015) from the field on 2023.
II. Locational data of the individual tree measured on the ground were collected with a hand-held GPS.
III. Landsat satellite data of 2001, 2008, 2016 and 2023 were used in calculating the vegetation indices and above-ground biomass.
IV. Digital Elevation model is used to show the elevation variation in Jorhat.

## 4. Software used

I. ERDAS (Image Processing Software) and QGIS (GIS software) has been used for the image processing, rectifying the images, landscape mapping and above ground biomass modeling.
II. ARGIS software has been used for overlay analysis, spatial analysis, data management and mapping.
III. R-statistic software was used for statistical analysis (https://cran.r-project.org/bin/windows/base/).

## 5. Methodology

### 5.1 Biomass estimation using field data

There are no local biomass maps with known accuracy or sufficient field data available to assess the biomass model. Therefore, field sampling through random method using a handheld GPS was applied to estimate biomass for individual trees. The tree diameter at breast height was measured in 2023. Approx of 50 tree sample were measured from each landscape's types. Diameter at breast height means the diameter of tree is measured at breast height, defined as 1.35 m up from point of ground at the tree base (Fig. 2).

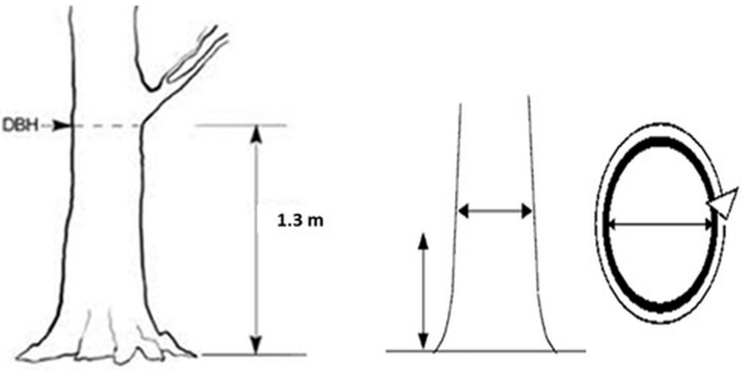


Fig. 2. Diameter at breast height

The circumference of a tree is measured and the diameter is calculated using equation shown below:

Circumference = π *diameter (where π = 3.14)

Or  Diameter = circumference/ π  Eq.1

The diameter at breast height is measured to use in the allometric equation model for above ground biomass estimation. Most of the research work revealed that AGB is strongly correlated with tree diameter. Also, it is accepted that simple model with only diameter as input is a good estimation of above ground biomass (Pragasan, 2014).

## Biomass estimation using remotely sensed data

A model that incorporates remotely sensed data and associated ancillary data has the potential to improve model performance and is more applicable to large study area (Lu, 2002).

The allometric regression models in this study were selected based on published literature considering the suitability of the

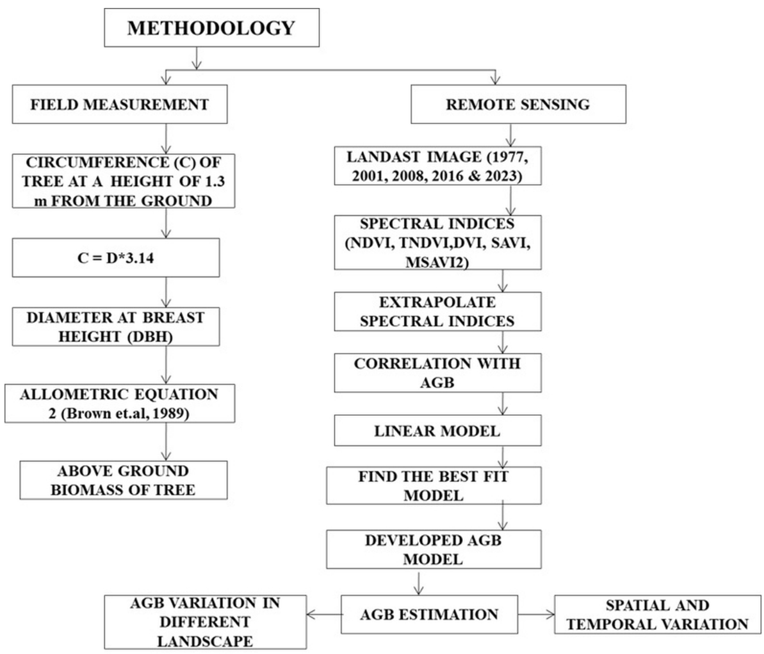


Fig. 3. Methodology flow chart

Table 1. Vegetation indices evaluated in this study

| Vegetation Index | Equation | Reference |
|---|---|---|
| DVI | DVI = (NIR-R) | Tucker et al. 1979 |
| NDVI | (NIR-R)/(NIR+R) | Rouse et al. 1973 |
| TNDVI | Sqrt((NIR-R)/(NIR+R)+0.5) | Deering et al. 1975 |
| SAVI | (1+L)*(NIR-R)/(NIR+R+L) with L=0.5 | Huete 1988 |
| MSAVI2 | (0.5)*(2*(NIR+1)-sqrt((2*NIR+1)2-8*(NIR-R))) | Qi et al. 1994 |

study area. Thus, the regression model (Brown et al, 1989, Equation 2.) was applied for field measurement.

$$AGB = 13.2579 - 4.8945 \times D + 0.6713\, D^2$$

Eq. 2. (Brown et al. 1989)

Where, AGB is above ground biomass and D is the diameter at breast height.

The biomass for each sample tree is calculated using allometric Equation 1. The sample AGB values are extrapolated to vegetation indices calculated from the Landsat satellite data of 2023.

In this study five vegetation indices (Table.1) were selected and their correlation with the estimated AGB using the allometric Equation 2 was calculated. Correlation analysis measures the degree of association between two or more variable (Singh and Das, 2014). The correlation with the AGB was calculated to determine the strength of these indices in relation to AGB. The index with the closest relation was used as independent variable in the AGB model development through a simple linear regression model method. Satellite based vegetation indices (Vis) models are the most commonly used models for estimation of biomass in many studies (Das and Singh, 2012).

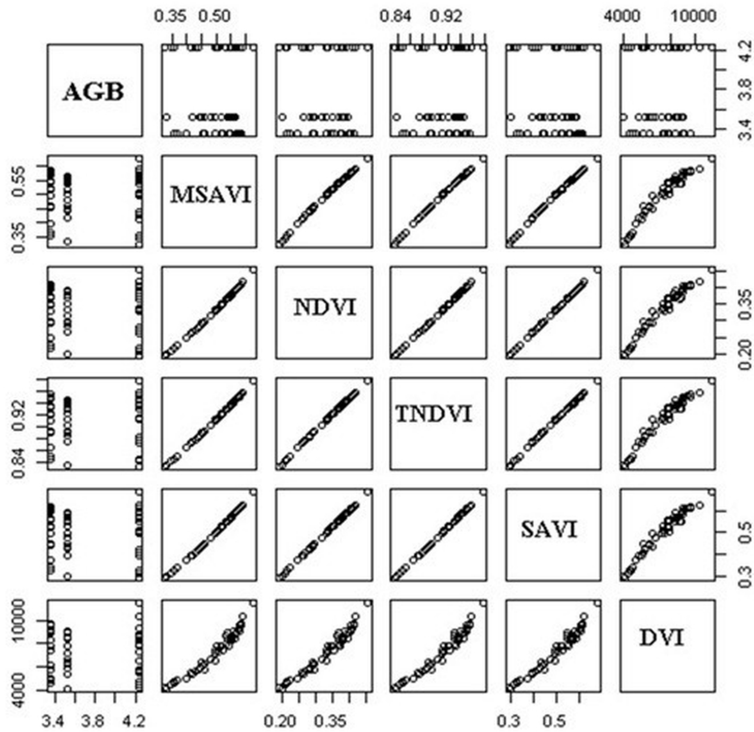


Fig. 4. Correlation Matrix of AGB and vegetation indices (MSAVI2, NDVI, TDVI, SAVI & DVI)

Table 2. Correlation coefficient (r) between vegetation indices and AGB

| Vegetation Indices | DVI | NDVI | TDVI | SAVI | MSAVI2 |
|---|---|---|---|---|---|
| Correlation coefficient (r) | 0.760 | 0.785 | 0.787 | 0.785 | 0.790 |

The results of correlation analysis between AGB and vegetation indices are presented in Table 2. The correlation values of the indices did not indicate significance differences. The highest significance is seen with MSAVI2(Figure 4 and Table 2). Among all the indices DVI correlation with the AGB was the lowest (r = 0.76). DVI has the ability to distinguish the soil and vegetation except in areas with a lot of shade. Hence, DVI does not give proper information when reflected wavelengths are affected due to topography, atmosphere or shadows (Tucker et al, 1979).

The MSAVI has the closest correlation with AGB (r = 0.790). The linear model function was used to obtain best fit correlation coefficient. The best fit correlation was seen in MSAVI2 (r = 0.790) with coefficient determination (R2 = 0.616). The result shows that there is strong correlation between AGB and MSAVI2. MSAVI2 eliminates the need to find the soil line from a feature-space plot or even explicitly specify the soil brightness correction factor (Qi et al., 1994). The soil background is a major surface component controlling the spectral behavior of vegetation canopies and on which the retrieval of biophysical characteristics of the canopy depends (Ahmad, 2012).

The MSAVI2 index showed the best regression fit with AGB and it was strongly significant (P = 8.9e-12, <0.01); hence it was subsequently used as predictor of AGB in the linear model of AGB. The AGB values dataset was used as the dependable variable and the MSAVI2 (Equation 3) as the independable variable in the linear regression model method.

$$Y = 6502.48*MSAVI - 31.05 \quad \text{Eq. 3}$$

Where, Y is the AGB and MSAVI2 is the calculated modified vegetation index image.

Based on the regression Equation 3, the model was run with landsat images (2001, 2008, 2016 and 2023) in Jorhat district for above ground biomass estimation and mapping.

## 6. Result:

### Distribution of above ground biomass:

The temporal and spatial changes in AGB are often linked to several environmental factors, including deforestation, land use patterns, climate change, and conservation efforts. In this paper, the temporal changes in AGB from 2001 to 2023, with particular attention to the factors that influence these changes. To estimate AGB, a combination of satellite data and ground-based measurements were used.

### *Temporal change of above ground biomass*

A time-series analysis was conducted for the years 2001, 2008, 2016 and 2023 (Fig. 5) which allowed for the identification of patterns and changes in biomass over time. Data from remote sensing was processed and analyzed to calculate AGB in tons per hectare (t/ha) for each year. Specific areas with varying levels of AGB were classified into different categories for a more detailed spatial analysis of biomass distribution.

The analysis of AGB (Above-Ground Biomass) over the period from 2001 to 2023 reveals notable fluctuations. Between 2001 and 2008, there was a modest increase in AGB, rising from 524.6 t/ha to 558.1 t/ha—an approximate 6.39% increase. However, this upward trend did not persist. From 2008 to 2016, AGB declined significantly by around 17.25%, dropping to 461.8 t/ha. The decreasing trend continued into 2023, with AGB further falling to 437.2 t/ha, marking an additional 5.33% decline from 2016. Overall,

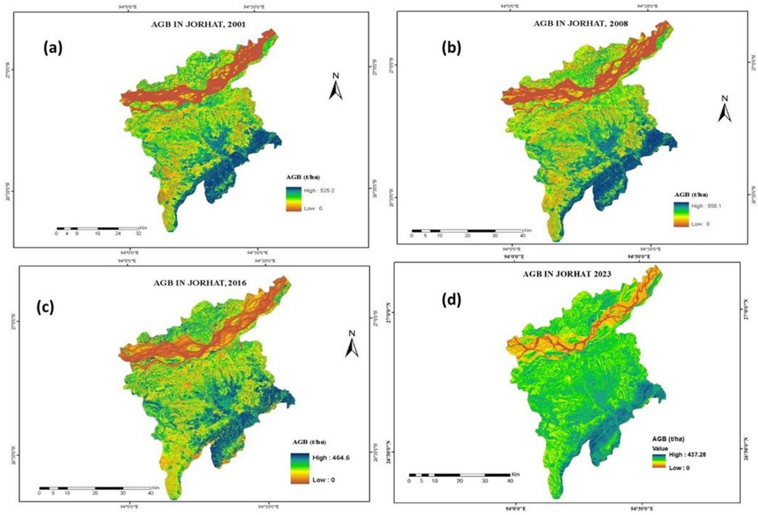


Fig. 3. Methodology flow chart

when comparing 2001 to 2023, there was a net decrease of approximately 16.66% in AGB. This downward trend is also reflected in the spatial distribution of biomass, as areas with AGB greater than 400 t/ha steadily diminished over time. By 2023, much of the biomass was concentrated in the 200–400 t/ha range, indicating a significant loss in high-biomass areas over the two-decade period. This suggests a gradual degradation of vegetative cover, with a shift towards areas of lower biomass density.

The subsequent decline from 2008 to 2023(Table 3) suggests rather than environmental conditions external pressures such as deforestation, agricultural expansion, and urbanization had a greater impact. The degradation of biomass in certain regions also points to reduced carbon storage capacity, contributing to higher $CO_2$ emissions in the atmosphere.

The analysis of low biomass areas from 2001 to 2023 reveals clear negative changes in forest health and biomass density. The steady expansion of land classified under the low biomass category highlights a degradation trend over time. In 2001, only 434 hectares were considered low biomass, representing a relatively small portion of the landscape. However, by 2008, this area had increased to 585 hectares—an early indication of declining biomass, with a 34.79% rise in low biomass coverage.

This negative trend became more severe in 2016, when the low biomass area more than doubled compared to 2001, reaching 976 hectares—a 124.88% increase, suggesting widespread biomass loss. By 2023, the situation had worsened further, with low biomass areas expanding to 1078 hectares, representing a total increase of 148.39% since 2001. This shift reflects a substantial degradation in vegetation density and

Table 3. Temporal Changes in AGB (t/ha)

| Years | Maximum AGB (t $ha^{-1}$) | AGB Decrease (t/ha) |
|---|---|---|
| 2001 | 524.6 | ------- |
| 2008 | 558.1 | -20 |
| 2016 | 461.8 | -91.1 |
| 2023 | 437.2 | -24.6 |

Table 4. Areas with different amounts of AGB from 2001 to 2023

| Years | 0<AGB (t ha$^{-1}$) ≤ 200 (Area in hectare) | 200<AGB (t ha$^{-1}$) ≤ 400 (Area in hectare) | AGB (t ha$^{-1}$) > 400 (Area in hectare) |
|---|---|---|---|
| 2001 | 434 | 824 | 1586 |
| 2008 | 585 | 1037 | 1230 |
| 2016 | 976 | 821 | 1055 |
| 2023 | 1078 | 992 | 782 |

ecosystem productivity. The increase of 644 hectares in low biomass land over the 22-year period indicates that a growing portion of the landscape is no longer supporting dense vegetation, which could have serious implications for carbon storage, biodiversity, and overall forest resilience.

### *Spatial Change of above ground biomass*

The area of land with moderate biomass exhibited both increases and decreases over the study period, reflecting its dynamic nature. In 2001, there were 824 hectares (Table 4.) of moderate biomass. By 2008, this area had increased to 1037 hectares, representing a 25.91% increase compared to 2001. However, this gain was not sustained. By 2016, the moderate biomass area declined to 821 hectares, marking a 20.84% decrease from 2008. Despite this drop, the area recovered slightly by 2023, increasing to 992 hectares, which represents a 20.84% increase from 2016. Comparing the start and end of the study period, the moderate biomass area grew modestly from 824 hectares in 2001 to 992 hectares in 2023, resulting in an overall increase of 20.39%. These percentage changes highlight how moderate biomass zones are susceptible to both degradation and recovery, influenced by ecological changes and human activity.

The high biomass category, which represents areas with the densest vegetation, showed a continuous and substantial decline throughout the study period. In 2001, high biomass areas covered 1586 hectares. By 2008, this had decreased to 1230 hectares—a 22.45% reduction in just seven years. The downward trend persisted into 2016, when the high biomass area dropped to 1055 hectares, marking a further 14.23% decrease from 2008. The most dramatic decline occurred by 2023, with high biomass areas shrinking to just 782 hectares, representing a 25.91% decrease from 2016.

Overall, from 2001 to 2023, the high biomass area declined by 804 hectares, equating to a total percentage loss of approximately 50.69%. This sharp reduction reflects significant degradation, likely due to deforestation, land-use change, or other environmental pressures. When viewed alongside the increase in low biomass areas, the data highlight a concerning shift in landscape structure, indicating a loss of dense vegetative cover and a decline in ecosystem health over the two-decade period.

The AGB in Jorhat district was high in the southern part of the Assam-Nagaland border while it is comparatively lower in the northern part of the district due to the existence of agricultural land. The Holongapar, Dessai valley and Tiru Hills possess highest AGB due to presence of more than 50% forest cover density. 40% of the total geographical land of Jorhat is under agriculture and 20% is under forest only. Predictably lowest AGB of 4 t/ha occurs within the built-up areas and riverside areas. The AGB was lower in the urban and peripheral areas of the town where the forest cover was substantially lower. The landscape-level variation physiographic, elevation and soil properties has significant control on production of biomass (Nave et al., 2017)

## Variation of above ground biomass in different landscape

### *Physiography*

The physiographic diversity (Fig.6) of the study area plays a critical role in determining the distribution of above-ground biomass (AGB). This analysis highlights significant spatial variation in AGB across different landforms, strongly influenced by topography, hydrology, and soil conditions.

Waterlogged areas such as marshes, swamps, and active floodplains exhibit the lowest AGB values, with biomass ranging from 13 t/ha to 25 t/ha. These areas, frequently inundated by water, have limited vegetation growth, as water saturation hampers root development and nutrient cycling. The consistent flooding in these low-lying zones also restricts forest cover and productivity, resulting in comparatively lower biomass accumulation.

Conversely, areas with greater elevation, such as the moderately steep to steep hills, demonstrate significantly higher AGB, reaching 90 t/ha. These hilly regions, despite covering only a small portion of the landscape (12,579 hectares), provide favorable conditions for forest growth, with well-drained soils and less frequent flooding. The Upper Piedmont and Undulating Upland (63 t/ha) and Gently Sloping Uplands (Dissected) (68 t/ha) also show substantial AGB, emphasizing the importance of topography in supporting vegetation. The forested slopes in these elevated areas allow for healthy biomass storage due to stable conditions that promote higher productivity.

The very gentle physiography, which covers the largest area (58,803 hectares), supports intermediate AGB levels (52 t/ha). Although less affected by flooding compared to lower floodplains and marshes, the more gradual slopes and proximity to watercourses moderate the level of biomass accumulation. Lower Piedmont (42 t/ha) and Inter Hill Valley (58 t/ha) demonstrate good biomass levels, indicating these landscapes can sustain relatively dense vegetation. Regions such as Active Flood (14 t/ha), Marshes and Swamps (13 t/ha), and Char Land (25 t/ha) reveal low AGB due to waterlogged conditions, which restrict tree growth and biomass accumulation. Lower Flood (28 t/ha) and Lower Terraces (35 t/ha)

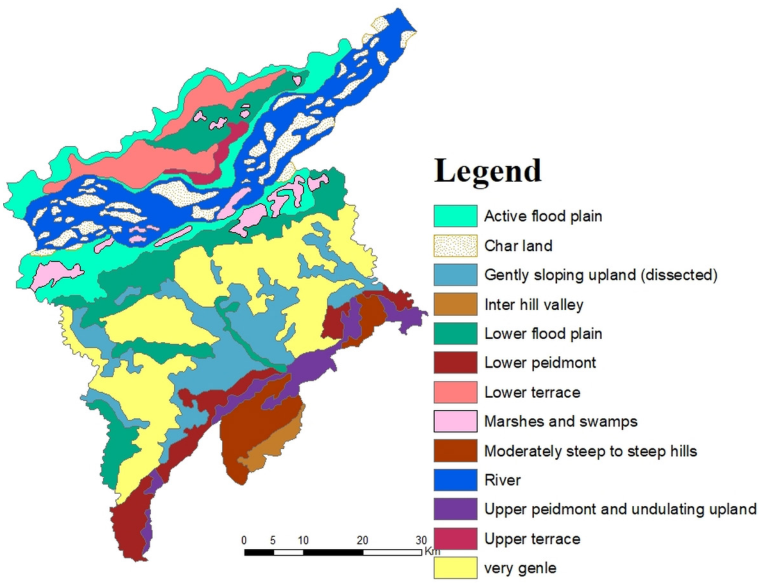


Fig. 6. Physiography map of Jorhat

Table 5. AGB distribution in physiography of Jorhat

| Sl. no | Physiography | Area (ha) | AGB(t / ha) |
|---|---|---|---|
| 1 | Char land | 16380 | 25 |
| 2 | Very gentle | 58803 | 52 |
| 3 | Active flood | 31983 | 14 |
| 4 | Lower flood | 35668 | 28 |
| 5 | Marshes and swamps | 8466 | 13 |
| 6 | Lower piedmont | 14438 | 42 |
| 7 | Lower terraces | 15251 | 35 |
| 8 | Upper terraces | 2653 | 29 |
| 9 | Inter hill valley | 3078 | 58 |
| 10 | Moderately steep to steep hill | 12579 | 90 |
| 11 | Upper piedmont and undulating upland | 10720 | 63 |
| 12 | Gently sloping uplands (dissected) | 35584 | 68 |

exhibit slightly better AGB compared to the most inundated areas but still face challenges related to soil fertility and drainage.

This physiographic analysis illustrates the clear relationship between elevation, water retention, and AGB. Waterlogged areas, which are prone to frequent flooding, demonstrate the lowest biomass potential, while elevated, forested regions accumulate the highest AGB. The results suggest that management and conservation strategies should account for these variations, particularly when addressing land-use practices and forest conservation.

### *Elevation*

Elevation is a critical environmental variable that significantly influences above-ground biomass (AGB) distribution. Previous studies, such as Rasel (2013), have shown a positive correlation between elevation and biomass, with higher elevations supporting greater biomass accumulation. Similarly, Limbu and Koirala (2011) found that high-altitude areas exhibit greater biomass productivity. The variation in elevation across a landscape can affect local climate, soil characteristics, and forest cover, all of which contribute to biomass distribution. Through this analysis it defines how elevation influences AGB in the Jorhat region, with specific emphasis on the relationship between elevation gradients (Fig.7), forest cover, and biomass content.

The southern part of Jorhat is home to four key Reserved Forests: Hollongapar Reserved Forest, Dessai Valley Reserved Forest, Tiru Hills Reserved Forest, and Geleki Reserved Forest. These forests have high forest densities, which directly contribute to their elevated AGB levels. In 2016, the forest density of these reserves was recorded as follows:

- Hollongapar Reserved Forest: 64% forest density, with 235 t/ha of AGB
- Dessai Valley Reserved Forest: 57% forest density, with 239 t/ha of AGB
- Tiru Hills Reserved Forest: 51% forest density, with 217 t/ha of AGB
- Geleki Reserved Forest: 47% forest density, with 187 t/ha of AGB

The relatively high forest density in these areas promotes greater AGB, with Hollongapar and Dessai Valley Reserved Forests showing the highest biomass values. The average diameter at breast height (DBH) of trees in these forests is 62 cm, further indicating the maturity and health of the forest stands in these elevated regions.

The direct influence of elevation on biomass

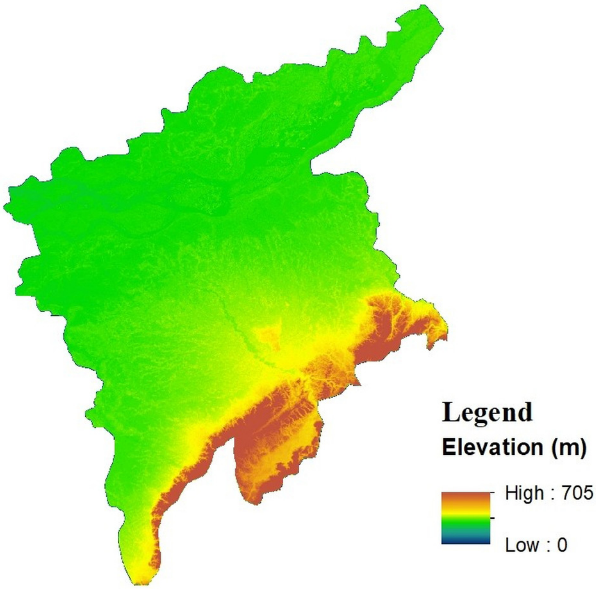


Fig. 7. Elevation map of Jorhat

distribution is evident when comparing AGB across different altitudes (Fig.8). In the southern region, where elevations reach up to 400 meters, AGB is measured at 82 t/ha. In contrast, in the northern areas, where the elevation is around 100 meters, AGB declines sharply to only 13 t/ha. This stark difference underscores the role of elevation in promoting favorable conditions for forest growth and biomass accumulation. Higher elevations are associated with cooler temperatures, better-drained soils, and reduced human interference, all of which contribute to greater forest density and higher AGB values.

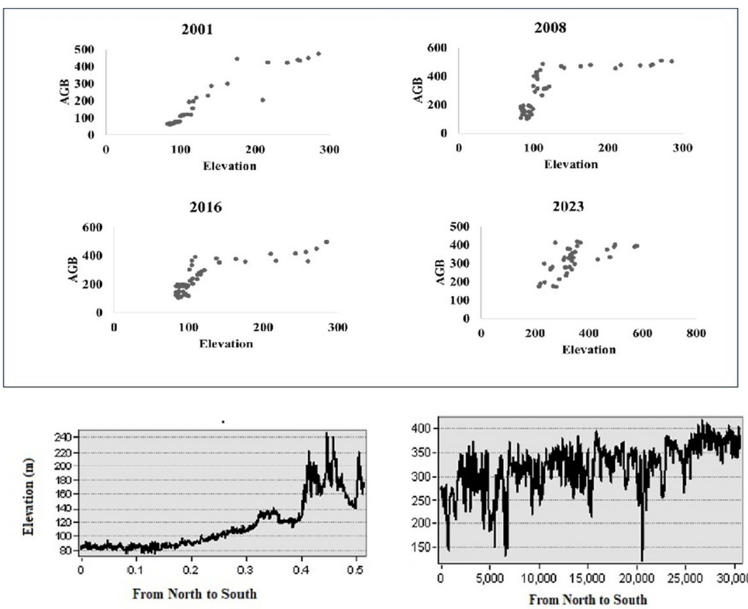


Fig. 8. AGB and Elevation realationship

Fig 7 shows the steep decline in AGB at lower elevations, especially in the north, is largely attributed to reduced forest cover and increased land-use pressures such as agriculture and settlement expansion. These low-lying areas are more prone to flooding and soil erosion, which further limits forest productivity and biomass accumulation.

### *Soil*

Soil characteristics play a critical role in determining vegetation growth, forest composition, and above-ground biomass (AGB) accumulation. In the Jorhat region, different soil types—ranging from younger and older alluvial soils to lateritic and red loamy soils—exhibit significant variations in their ability to support forest ecosystems and biomass production.

The northern areas of Jorhat are predominantly covered by younger alluvial soils (Fig. 8), which are formed by more recent deposits from the Brahmaputra River. These soils tend to be finer, less compact, and moderately fertile, but they exhibit lower AGB compared to older alluvial soils found in the southern tracts of the region. In contrast, the old alluvial soils in the southern part are well-developed, deep, and highly fertile, supporting larger trees with robust root systems.

The old alluvial soils in the south range (Fig.9) from brownish to yellowish-brown in color and vary in drainage capacity from imperfectly drained to well-drained. These soils are fine-loamy to coarse-loamy in texture, providing optimal conditions for large canopy trees that contribute to higher AGB. In contrast, younger alluvial soils are less developed and support fewer large trees, leading to lower AGB values.

In addition to alluvial soils, smaller areas of the region are covered by lateritic and red loamy soils, which are less fertile and support lower biomass due to poor structure and nutrient availability. These soil types are

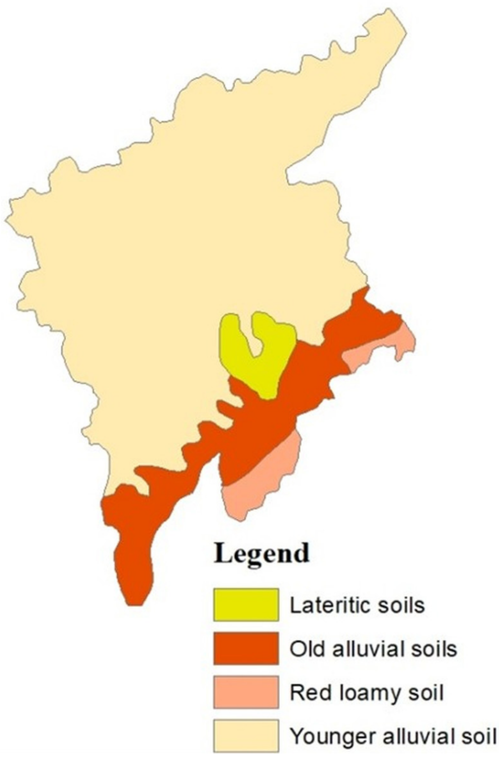


Fig. 9. Soil map of Jorhat

Table 6. AGB distribution in the different soil type of Jorhat

| Sl.No | Soil Type | Area | AGB (t/ha) |
|---|---|---|---|
| 1 | Lateritic soils | 10418.70 | 56.34 |
| 2 | Red loamy soil | 10266.89 | 85.72 |
| 3 | Younger alluvial soil | 216731.00 | 114.27 |
| 5 | Old alluvial soils | 44553.20 | 97.84 |

primarily located in areas with hilly terrain or where the soil formation processes limit root development and tree growth (Fig.8).

The AGB distribution across Jorhat varies significantly based on soil type. The old alluvial soils, which are deep, fertile, and well-drained, support the highest AGB in the region, with large canopy trees and dense forest cover. These soils offer optimal growing conditions, allowing for extensive root systems and tree growth, contributing to greater biomass accumulation. As noted by Quesada et al. (2012) and Scaranello et al. (2016), well-structured, deep soils promote root development and tree canopy expansion, which are key factors in high AGB content.

In contrast, younger alluvial soils, which cover a larger portion of the region, have a slightly lower AGB content. Despite being fertile, these soils are less well-developed than older alluvial soils and support a lower density of large trees. As a result, the AGB in areas with younger alluvial soils is recorded at 114.27 t/ha, which is notably lower than in regions with older alluvial soils, though still higher compared to areas with less fertile soils.

Lateritic and red loamy soils, which cover much smaller areas in Jorhat, support considerably lower AGB due to their poor nutrient content and structure. Lateritic soils, in particular, are known for their iron-rich composition, which leads to poorer fertility and restricted tree growth. As a result, the AGB in areas with lateritic soil is 56.34 t/ha, while regions with red loamy soils exhibit slightly higher AGB at 85.72 t/ha (Table 6). The limited productivity of these soils results from weak soil structure, which restricts root growth and reduces the overall canopy density.

The spatial distribution of soil types and their corresponding AGB content highlights the strong relationship between soil fertility, structure, and biomass production. Old alluvial soils, which are concentrated in the southern part of Jorhat, support the largest trees and highest AGB, demonstrating the vital role of fertile, well-drained soils in promoting forest productivity. These soils allow for robust tree root systems, leading to dense forest cover and higher biomass accumulation.

In contrast, areas with younger alluvial soils, despite covering a larger portion of the region, exhibit slightly lower AGB. This is likely due to the more recent formation of these soils and their moderate drainage and fertility levels, which limit their ability to support extensive tree growth. The lower AGB content in lateritic and red loamy soils further underscores the importance of soil fertility and structure in determining forest composition and biomass. Old alluvial soils in the southern part of the region provide optimal conditions for forest growth, resulting in higher AGB, while younger alluvial soils, though extensive, support lower biomass. Poorly structured soils, such as lateritic and red loamy soils, contribute to reduced AGB due to their limited fertility and restricted root development.

## 7. Conclusion

This study provides a comprehensive assessment of above-ground biomass (AGB) across temporal and spatial dimensions in Jorhat, offering valuable insights into the dynamics of biomass distribution and its driving factors. The temporal analysis reveals a clear and concerning decline in AGB over the past two decades. Notably, areas with high AGB (>400 t/ha) decreased from 1586 hectares in 2001 to just 782 hectares in 2023—a 50.69% reduction. Concurrently, low biomass areas (AGB < 200 t/ha) expanded from 434 hectares in 2001 to 1078 hectares in 2023, reflecting a 148.39% increase. While moderate biomass zones showed some fluctuation, they remained relatively stable, ending with a 20.39% net increase over the study period. These shifts suggest ongoing forest degradation, likely driven by land-use changes, deforestation, and other anthropogenic pressures.

Spatially, the analysis demonstrates that physiographic features—particularly elevation and topography—are key determinants of biomass distribution, with higher elevations generally supporting denser vegetation cover. However, to deepen our understanding of biomass variation, future research should incorporate additional biophysical parameters such as soil moisture, temperature, and precipitation. These factors can help refine predictive models and offer insights into how climate variability interacts with landscape features to influence forest structure and health.

In light of these findings, the study strongly supports the need for enhanced conservation strategies. To move from analysis to action, specific recommendations include: implementing afforestation and reforestation programs in degraded zones, enforcing land-use regulations to limit forest conversion, and promoting community-based forest management. Additionally, integrating these findings into existing policy frameworks—such as India's National Forest Policy and REDD+ initiatives—can support evidence-based decision-making for sustainable forest governance.

Contextualizing these regional trends within broader national and global patterns of biomass loss strengthens the urgency of this issue. Similar declines are observed in tropical and subtropical forest systems worldwide, indicating that local actions can contribute meaningfully to global forest conservation goals. Ultimately, this study not only advances our understanding of AGB dynamics but also provides a foundation for targeted, data-driven policy interventions aimed at preserving forest and enhancing forest ecosystem resilience in the face of ongoing environmental change.

## 8. References

Brown, S., Gillespie, A.J.R. and Lugo, A.E. (1989): Biomass estimation methods for tropical forests with applications to forest inventory data. Forest Science. 35: 881-902.

Chhetri, D.B.K. and Fowler, G.W. (1996): Estimating diameter at breast height and basal diameter of trees from stamp measurements in Nepal's lower temperate broad-leaved forests. Forest Ecology and Management, 81:74-84.

Das, S. and Singh, T.P. (2012): Correlation analysis between biomass and spectral vegetation indices of forest ecosystem. International Journal of Engineering Research & Technology. 1, 5:1-13.

Das, B., Bordoloi, R., Deka, S., Paul, A., Pandey, P. K., Singha, L. B., … Mishra, M. (2021). Above ground biomass carbon assessment using field, satellite data and model based integrated approach to predict the carbon sequestration potential of major land use sector of Arunachal Himalaya, India. Carbon Management, 12(2), 201–214. https://doi.org/10.1080/17583004.2021.1899753

Deering, D.W., Rouse, J.W., Haas, R.H. and Schell, J.A. (1975): Measuring "Forage Production" of Grazing Units From Landsat MSS Data. Proceedings of the 10th International Symposium on Remote Sensing of Environment. II: 1169-1178

Dixon, R.K., Trexler, M.C., Wisniewski, J., Brow, S., Houghton, R.A. and Soloman, A.M. (1994): Carbon pools and flux of global forest ecosystems. Forest Science. 263( 3), 185-190.

B. GOSWAMI, R. HUSSAIN, V.U.M. RAO, & U.S. SAIKIA. (2016). Impact of climate change on rice yield at Jorhat, Assam. Journal of Agrometeorology, 18(2), 252–257.

Halperine, J., LeMay, V., Chindumayo, E., Verchot, L., Marshall, P. (2016). Model-based estimation of above ground biomass in the miombo eco region of Zambia. Forest Ecosystems. Springer.

3(14).

Huete, A. R., Justice, C., & van Leeuwen, W. (1996): MODIS vegetation index (mod13).

Limbu, D.K And Koirala, M. (2011): Above ground and Below ground Biomass situation of

Milke Jaljale Rangeland at Different Altitudinal Gradient. Our Nature. 9,107-111

Li M, Li X, Liu S, Lyu X, Dang D, Dou H, Wang K. (2022): Analysis of the Spatiotemporal Variation of Landscape Patterns and Their Driving Factors in Inner Mongolia from 2000 to 2015. Land. 11(9),1410. https://doi.org/10.3390/land11091410.

Lu, D., Mausel, P., Brondizio, E. and Moran, E. (2002): Above-ground biomass estimation of successional and mature forest using TM images in the Amazon basin.Advances in spatial data handling. 10th International symposium on spatial data handling. 183-196.

Magalhas, T.M and Seifort, T. (2015): Estimation of Tree biomass, Carbon stock and Error Propagation in Mecrusse Woodlands. Open Journal of Forestry. 5,471-488.

Nave, L.E., Gough, C.M., Perry, C.H., Hofmeister, K.L., Moine, J.M., Domke, G.M., Swanston, C.W., Nadelhoffer, K.J. (2017): Physiographic factors underlie rates of biomass production during succession in Great Lakes Forest landscapes, Forest Ecology and Management. 397,157-173.

Osuri, A.M., Madhusudan, M.D., Kumar, V.S., Chengappa, S.K., Kushalappa, C.G., Sankaran, M. (2014): Spatio-temporal variation in forest cover and biomass across sacred groves in a human-modified landscape of India's Western Ghats. Biological Conservation. 178, 193-199. ISSN 0006-3207. https://doi.org/10.1016/j.biocon.2014.08.008.

Pragasan, LA. (2014): Carbon stock assessment in the vegetation of the Chitteri reserve forest of the Eastern Ghats in India based on non-destructive method using tree inventory data. Journal Earth Science: Climate change, 1-9.

Qi, J., Chehbouni, A., Huete, A.R., Kerr, Y.H. and Sorooshian, S. (1994): A modified soil adjusted vegetation index. Remote sensing Environment. 48:119-126

Quesada, C.A., Phillips, O.L., Schwarz, M., Czimczik, C.I., Baker, T.R., Czimczik,C., Fyllas, N.M., Martinelli, L., Nardoto, G.B., Schmerler,J.( 2012): Basin-wide variation in Amazon forest structure and function are mediated by both soils and climate. Biogeoscience. 9, 2203-2246.

Rasel, S.M.M. (2013): Effect of elevation and above ground biomass (AGB) on soil organic carbon (SOC): A remote sensing-based approach in Chitwan district, Nepal. International Journal of Scientific & Engineering Research. 4(9).

Rawat, J.S. and Kumar, M. (2015): Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarkhand, India. The Egyptian journal of remote sensing and space sciences. 18, 77-84.

Rouse, J. W., Haas, R. H., Jr., Schell, J. A., & Deering, D. W. (1974): Monitoring vegetation systems in the Great Plains with ERTS. Third ERTS-1 Symposium, Washington, DC: NASA. 309-317.

Roy, P., Mohanty, A.K., Misra, M. (2023): Prospects of carbon capture, utilization and storage for mitigating climate change. Environmental Science Advances. 2(3), 409-423, ISSN 2754-7000, https://doi.org/10.1039/d2va00236a.

Saatchi1, S., Malhi, Y., Zutta, B., Buermann, W., Anderson, L.O., Araujo, A.M., Phillips, O.L., Peacock, J., Steege, H., Lopez Gonzalez, G., Baker,T., Arroyo, L., Almeida, S., Higuchi, N., Killeen, T., Monteagudo, A., Neill, D., Pitman1,N., Prieto, A., R. Salom, R., Silva, N., Asquez Mart´ ınez, R.V., Laurance, W., and Ram´ ırez, H.A. (2009): Mapping landscape scale variations of forest structure, biomass, and productivity in Amazonia. Biogeosciences Discuss. 6, 5461–5505, www.biogeosciences-discuss.net/6/5461/2009/

Sahariah, J., Kalita, S. and Baruah, B.K. (2015): An assessment of Land use-land cover change using geoinformatics in Sonai-Rupai wildlife sanctuary, Assam, India. Journal of Environmental Research and Development. 9(4), 1257-1262.

Shahina, N.N. (2025). Indian Population, Forest Degradation, and Its Management. In: Shukla, G., Manohar K., Raj Kizha, A., Panwar, P., Chakravarty, S. (eds) Forest Degradation and Management. Forestry Sciences, vol 87. Springer, Cham. https://doi.org/10.1007/978-3-031-84055-5_19

Scaranello, M. A. S., Castro, B. S., Farias, R. A., Vieira, S. A., Alves, L. F., Robortella, H. S., & Aragão, L. E. O. C. (2016): The role of stand structure and palm abundance in predicting above-ground biomass at local scale in southern Amazonia. Plant Ecology & Diversity. 9(4), 409–420. https://doi.org/10.1080/17550874.2016.1264015

Singh, T.P., Das, S. (2014): Predictive Analysis for Vegetation Biomass Assessment in Western Ghat Region (WG) Using Geospatial Techniques. J Indian Soc Remote Sens. 42, 549–557. https://doi.org/10.1007/s12524-013-0335-7

Tucker, C.J. (1979): Red and photographic infrared linear combination for monitoring vegetation. Remote sensing Environment. 8, 2:127-150.

Wani, A.A., Joshi, P.K., Singh, O and Pandey, R. (2012): Carbon Inventory Methods in Indian Forests-A Review. International Journal of Agriculture and Forestry. 2( 6), 315-323.

Wigley, T.B and Roberts, T.H. (1997): Landscape-level effects of forest management on faunal diversity in bottomland hardwoods. Forest Ecology and Management. 90(2-3), 141-154.

Wondem, S.A. (2015). Estimating above ground biomass and carbon stock of four national forets in Amhara region, Ethiopia. Thesis. University of Natural resources of Life science (BOKU) Vienna, Austria.