SatSure

White Paper

Estimating Biomass & Carbon Sequestration Potential for Forests and Croplands using Geospatial Analysis

CONTENTS

Glossary

- **MRV** – Measuring, Reporting and Verification
- **REDD+** - Reducing Emissions from Deforestation and Forest Degradation
- **SOC** – Soil Organic Carbon
- **SOM** – Soil Organic Matter
- **SDGs** – Sustainable Development Goals
- **IPCC** – Intergovernmental Panel on Climate Change
- **DBH** – Diameter at Breast Height
- **FSI** – Forest Survey of India
- **NDVI** – Normalized Difference Vegetation Index
- **EVI** – Enhanced Vegetation Index
- **LAI** – Leaf Area Index
- **GIS** – Geographic Information System
- **LULC** – Land Use Land Cover
- **Ha** – Hectare
- **t Ha-1** Tonnes Per Hectare
- **GHGs** – Green House Gases
- **SOCI** – Soil Organic Carbon Index
- **DEM** – Digital Elevation Model
- **SEA** – SouthEast Asia
- **MEA** – Middle East Asia
- **MIT** – Massachusetts Institute of Technology
- **ADB** – Asian Development Bank

Background

In a practical **application of geospatial technology**, the forest standing biomass & carbon measuring, reporting and verification (MRV) structure to back the climate change mitigation policies, such as REDD+, needs estimates of forest standing biomass & carbon, by way of an effort to estimate emissions.

A mixture of field inventory data and geospatial technology remains expected to provide that information. By connecting the satellite data sets and forest inventory data, we will develop the statistical models for total standing biomass & carbon estimation related to the satellite data spectral variability. We will estimate the **total standing forest biomass & carbon stock** of the entire study area. Also, the **near real-time information of Soil Organic Carbon (SOC)** is essential and crucial in the present context as it is the critical factor of soil organic matter (SOM).

It's one of the key suppliers to food production, extenuation and adaptation to the climate change context, and achieving the **Sustainable Development Goals (SDGs)**. SOC plays a significant role in soil functions and food production systems. Also, in a natural process, the mineralisation of SOC will be a valuable basis for the emissions of greenhouse gases.

Altering the contents of the SOC will individually change the establishment of ecosystem facilities essential for crop production and disturb the soils' ability to safeguard against environmental variations, as it helps in the regulations of the pliability of cropping systems against climate change.

We will use geospatial technology and ground inventory data to develop the statistical data sets linking with different spectral band combinations and indices. It will estimate the total SOC patterns in the cropland areas of the entire study area.

Forest Conservation and Carbon Assessment

Introduction

Ecological balance is key to the survival of living organisms while sustenance of natural resources and habitats is the key for maintaining ecological balance. **Forests are critical components of our ecosystem and play a major role in offsetting excess carbon, through soil and biomass level sequestration**.

The ever-growing need for food (with a growing population), industrialisation, and urbanisation has led to significant deforestation, causing depletion in forest cover. This has resulted in a high negative impact on our climate (IPCC, 2007a; Vitousek et al., 1997; Dadhwal et al., 2009) (Figure-1).

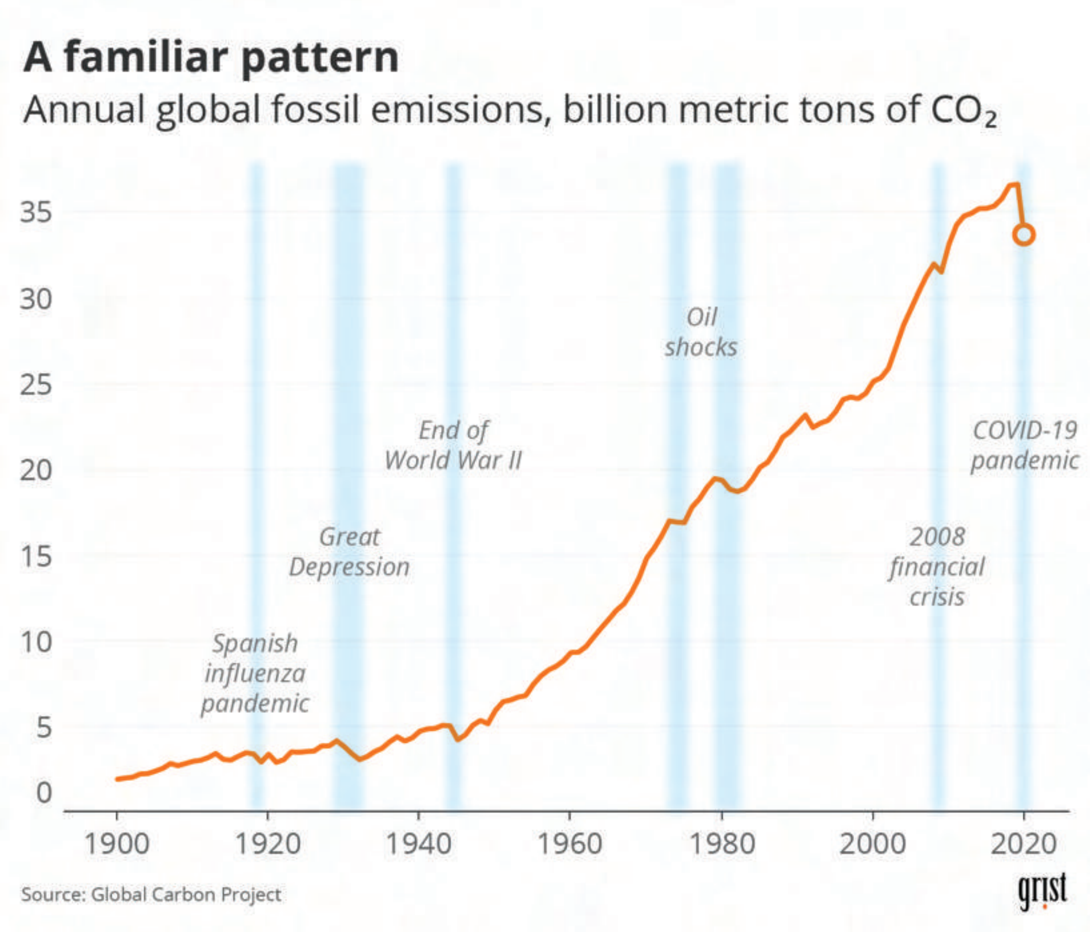


Figure-1: Trend of annual fossil fuel emissions

Setting the Context

Human-induced changes supplement greenhouse gases and change the earth's atmosphere (IPCC, 2003; 2007a). Biomass is one of the essential indicators for understanding how forest ecosystems function and their role in terrestrial vegetation carbon pools and the global carbon cycle under climate change (Darke et al., 2002; Xiao et al., 1997). Recently, forest biomass-related studies have become highly significant globally due to growing concerns about global warming and the forest carbon credit system (Houghton, 1991; Dadhwal et al., 2009).

It is essential to monitor and map the forest area to reduce global warming and get timely information on the afforestation programs and bring more area under green cover.

SatSure's Commitment towards Sustainability

At SatSure, we understand that direct measurement of forest biomass in the field could be a destructive method for assessing forest biomass. It is especially not economical in the case of old-growth forests, in the protected and restricted areas. This approach requires initial harvesting of entities over a varied range of size and girth classes to start a functional link between biomass and easily measurable plant parameters, such as diameter/ girth and height (Kale et al., 2004; Kale and Roy, 2012; Patil et al., 2012; Tiwari, 1994).

Therefore, we recommend leveraging allometric equations that approximate biomass of the tree component, or the total biomass of a single standing tree, based on easily measured variables, such as diameter/girth at breast height (dbh) and the height of the tree (FSI, 1996) (Figure-2).

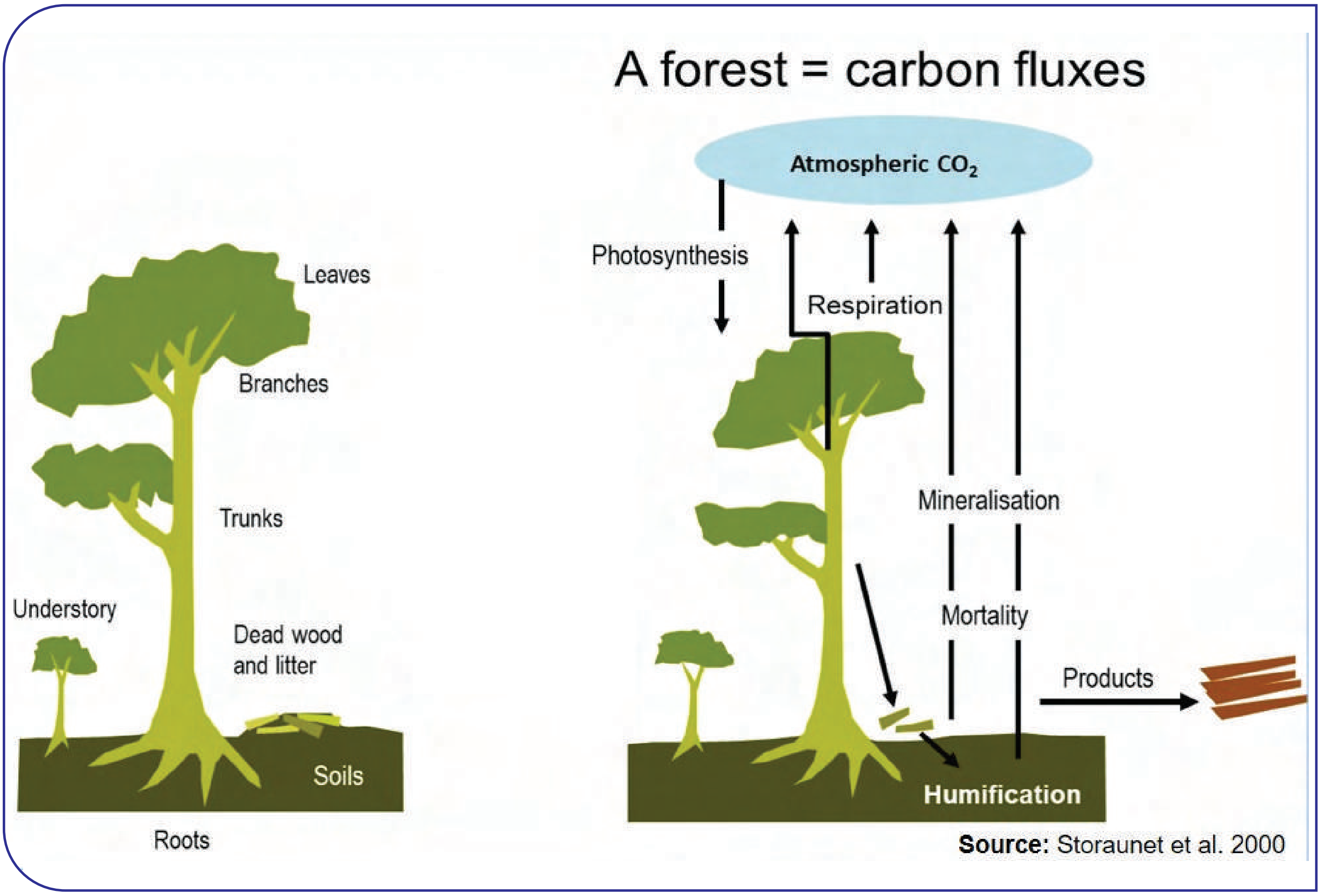


Figure- 2: Showing the carbon cycle and different tree parameters

SatSure's Monitoring and Reporting Solution

The non-destructive approach adopted by SatSure involves the application of component-wise equations for different species through the sampling of tree components, including bole, branch, twigs and leaves (Tiwari, 1994) (Figure-3). Recently, in many case studies globally, geospatial technology has been utilised for biomass and productivity estimation at local and regional levels. The biomass assessment solution has three key components: ground measurements, remote sensing and geographic information system (Lu, 2005).

The vast arrays of earth observation systems have opened several opportunities for quick and consistent assessments for monitoring above-ground standing biomass and carbon pools. Recently, efforts have been made to ensure the complete utilisation of geospatial datasets to estimate standing forest biomass and carbon (Patil et al., 2012; Tiwari, 1994).

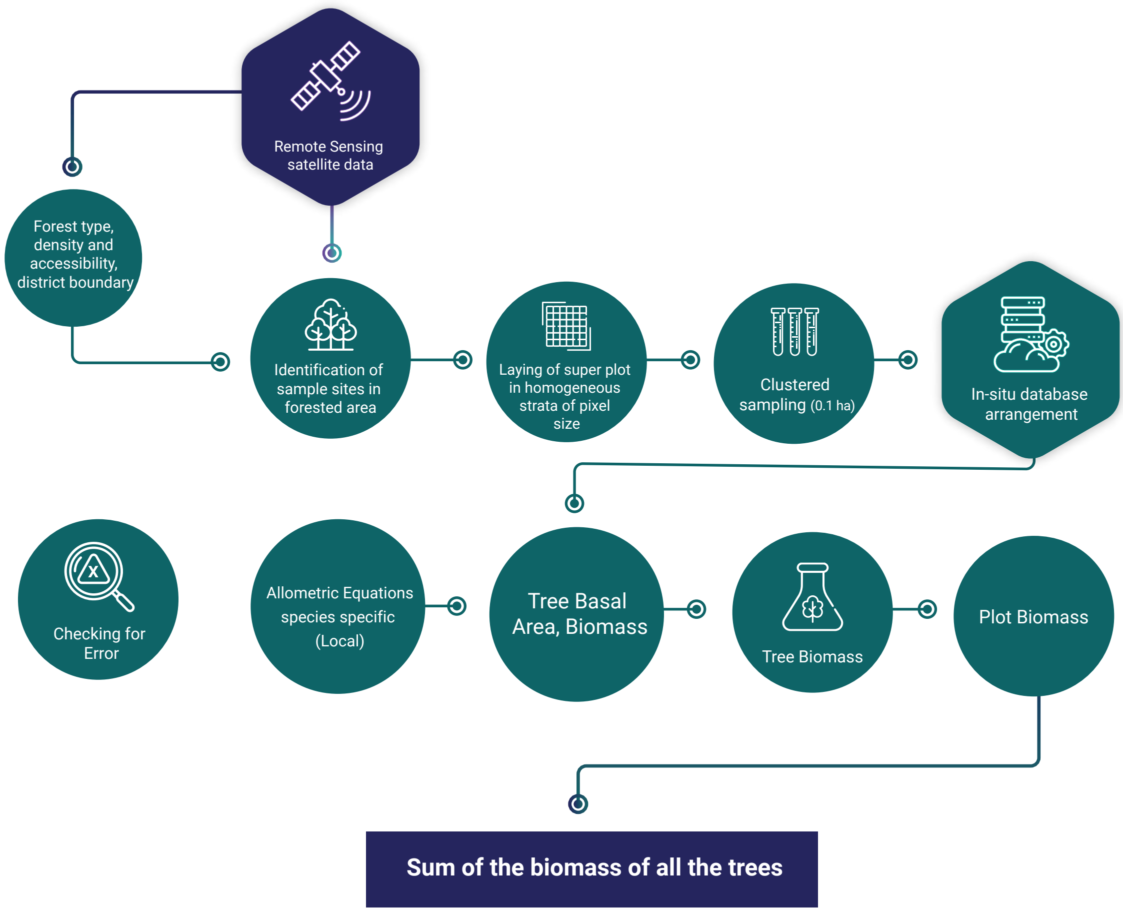
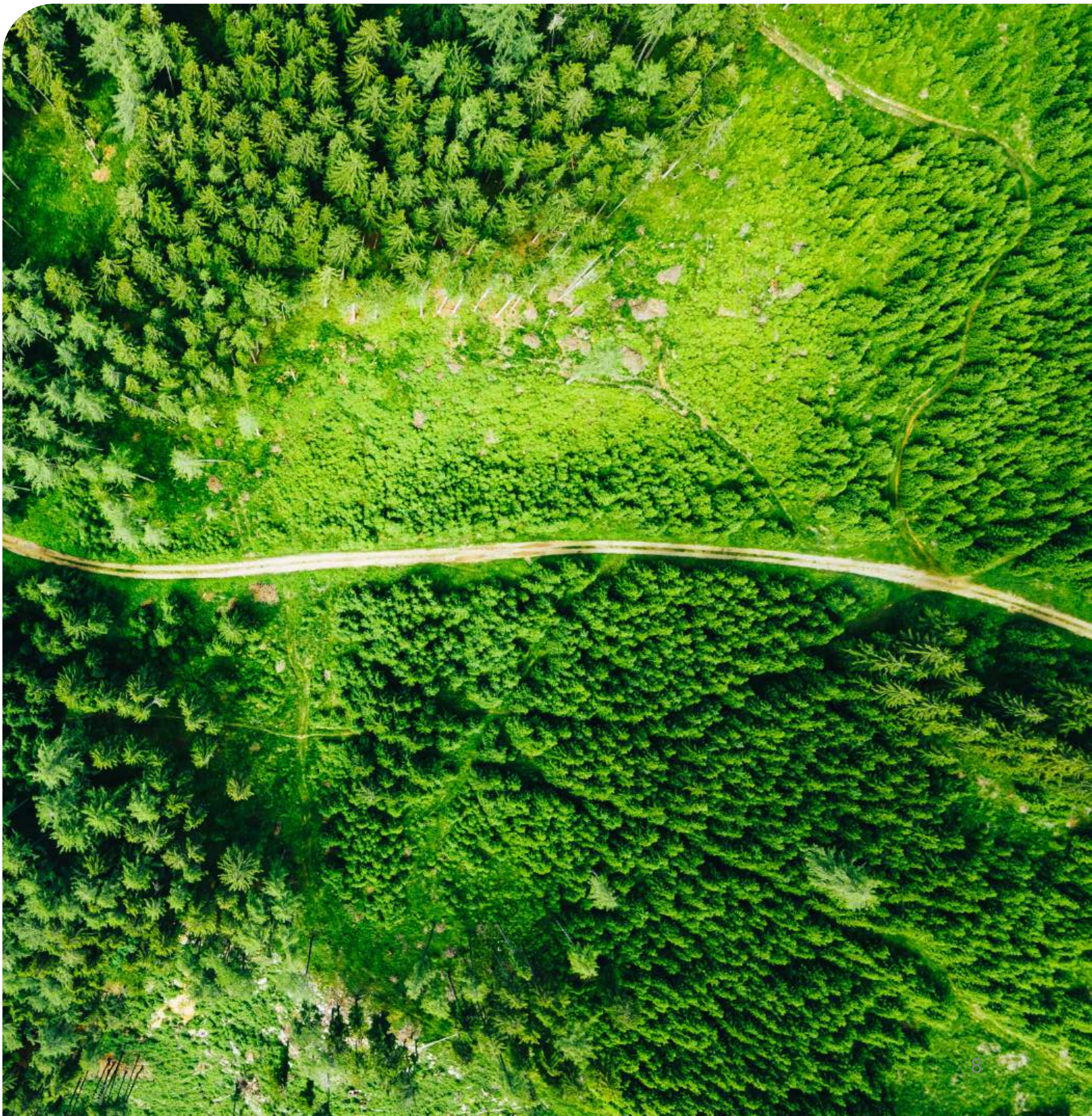


Figure- 3: Showing the non-destructive approach for standing biomass & carbon estimation

The vegetation indices, e.g. NDVI, EVI, LAI, are proved to be a good indicator of canopy cover, which has been an excellent correlation to biomass and productivity (Patil et al., 2012; Prince and Goward, 1995). Using satellite data and field measurements, this approach primarily aims to estimate the biomass and carbon pools in the selected study area. The solution also entails spectral models to produce a geospatial distribution of forest biomass and carbon stock.



Technology Overview

i. **Ground sampling** is conducted for mapping vegetation cover type and density. A two-stage nested clustering approach is being followed to collect the in-situ data (Figure-4).

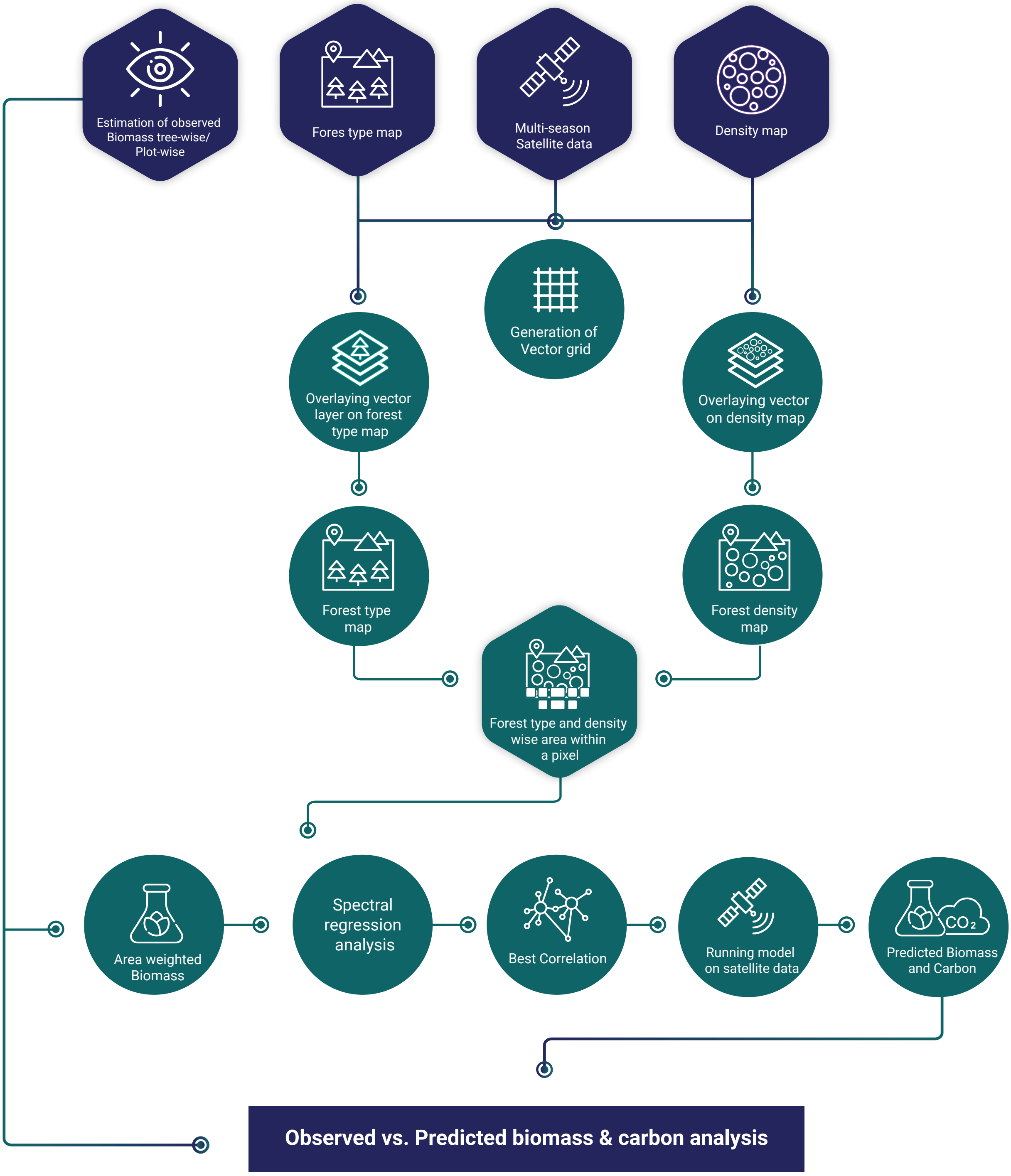


Figure- 4: The methodology followed for the standing biomass & carbon estimation

ii. Sample plots of 0.1 ha are laid. A total of 0.1ha sampling intensity is covered in the selected study area within different forest types, topography or aspects.

iii. The **biomass parameters** such as dbh (cm) at 1.37 m above ground and tree height (cm), compositions, density, percent canopy-covered are recorded for each sampling unit. The **vegetation indices**, e.g. NDVI, EVI and LAI, are proven to be a good indicator of canopy cover, which has been an excellent correlation to biomass and productivity (Patil et al., 2012; Prince and Goward,1995). Using satellite data and field measurements, this approach primarily aims to **estimate the biomass and carbon pools** in the selected study area. The solution also entails spectral models to produce a **geospatial distribution of forest biomass and carbon stock**.

iv. A **standard conventional non-destructive method** is followed to **estimate biomass**. This method involves the estimation of biomass of individual trees through allometric equations using dbh and height of the trees.

v. The site and species-specific allometric equations are gathered (leveraging available literature).

vi. Biomass of each of the four components: bole, branch, twig and leaf, is estimated using an allometric equation. The biomass of all trees within a plot will be aggregated and **total plot biomass is estimated**.

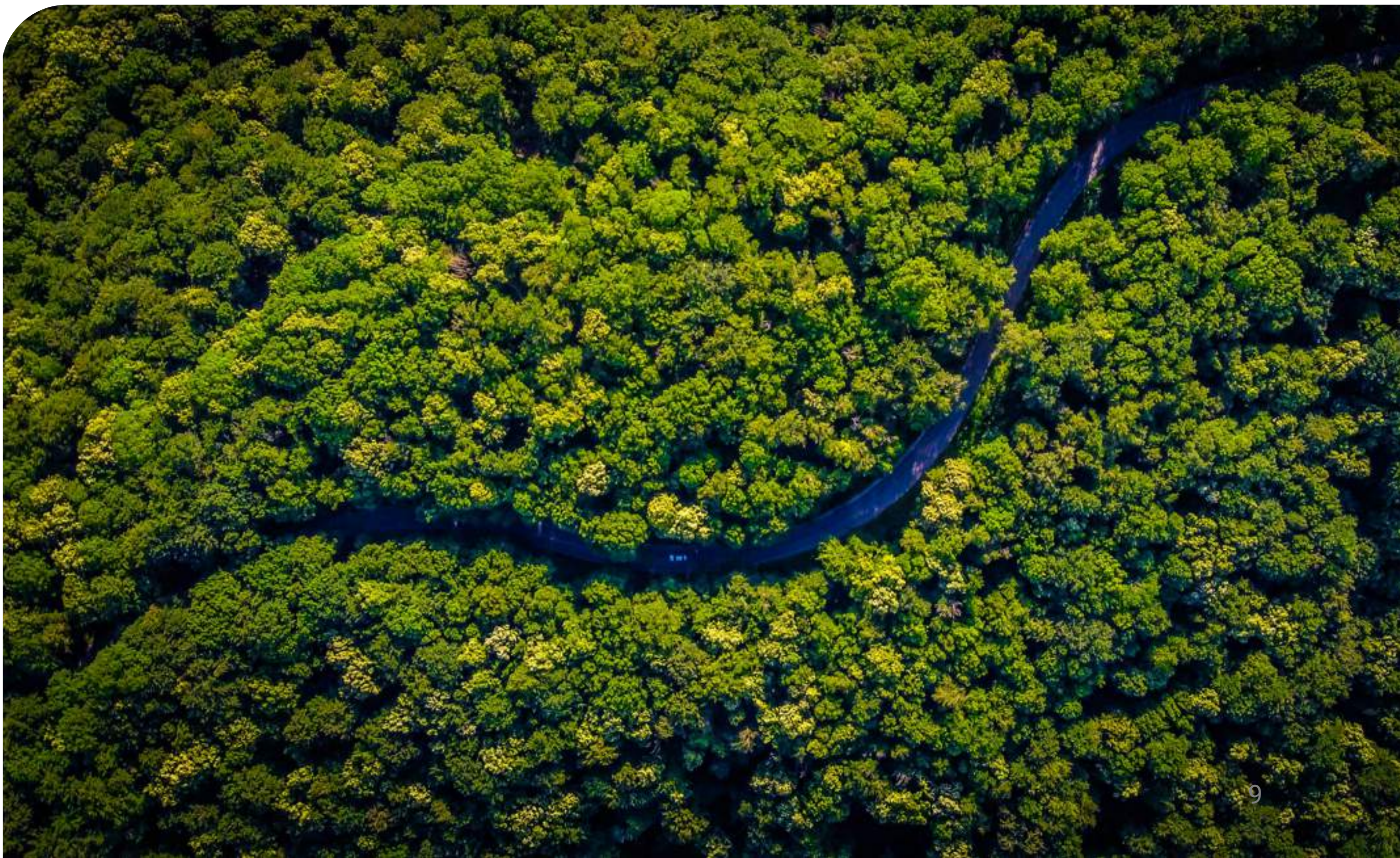
vii. **High-resolution satellite data** is used to **create vector boxes** around the sampling sites in the GIS domain. These vector boxes are then overlaid on the **density map**.

viii. **Visual interpretation of data** within each vector box for mapping for vegetation cover type/ land use and density is carried out using field points. The proportionate area of each land use/ land cover occurring within the vector boundary is obtained by getting the proposition between the areas inhabited by the particular LULC classes within the location of the pixel boundary in hectares.

ix. Classes such as water bodies and settlements are given zero weight. The forested area is multiplied by respective biomass to obtain total biomass for that type for that area. Subsequently, each land use/ land cover class's area weight is multiplied by the corresponding biomass of the respective class. Thus, biomass obtained for all the vegetation types belonging to different forest type-wise density classes occurring within the vector boundary of the pixel is summed up to get weighted biomass (t Ha1) within the respective pixels.

x. **Spectral modelling** is carried out to map biomass and up-scaling plot observations into a regional scale by correlating it with the reflectance of multi-season satellite data. Correlation coefficients are obtained for biomass estimation as a function of satellite-derived parameters viz., red and infrared reflectance and NDVI. In spectral modelling, multi-season images are used to establish a correlation between area-weighted biomass and satellite-derived parameters.

xi. The linear and nonlinear statistical models will be obtained to relate biomass to the data from different bands and indices (Red, Infrared and NDVI). The best fit model is selected based on high R2 values (also called coefficient of determination) and their significance. The best-fit model obtained estimates the biomass and carbon for the entire study area. Carbon content in vegetation is taken as 47.5 per cent of the above-ground biomass.



Carbon Sequestration Assessment of Agricultural Lands and Measuring Regenerative Carbon Potential

Introduction

Agriculture accounts for approximately 10% of all GHGs, and it is essential to estimate and note the carbon sequestration. Therefore, there is a need to adopt sustainable agricultural practices, which will also contribute to achieving SDGs.

Soil Organic Carbon (SOC) is vital for soil fertility and agricultural productivity (Lal, 2006; Reeves, 1997). Soil erosion causes a decline in SOC, resulting in economic losses due to decreased crop productivity (Lal, 2004; West and Post, 2002). This creates an additional need to supplement degraded soils with chemical fertilisers (Pimentel et al., 1995), further adding input costs.

Setting the Context

The influence of SOC on agricultural productivity has in part, driven interest in the development of digital soil mapping techniques (Bachofer et al., 2015; Chen et al., 2000; Dogan and Kılıç, 2013; Frazier and Cheng, 1989; Mishra et al., 2009; Mulder et al., 2011).

Digital soil mapping techniques use diffuse reflectance spectroscopy, which has been demonstrated to accurately and non-destructively relate spectral reflectance to soil properties (Figure-5)

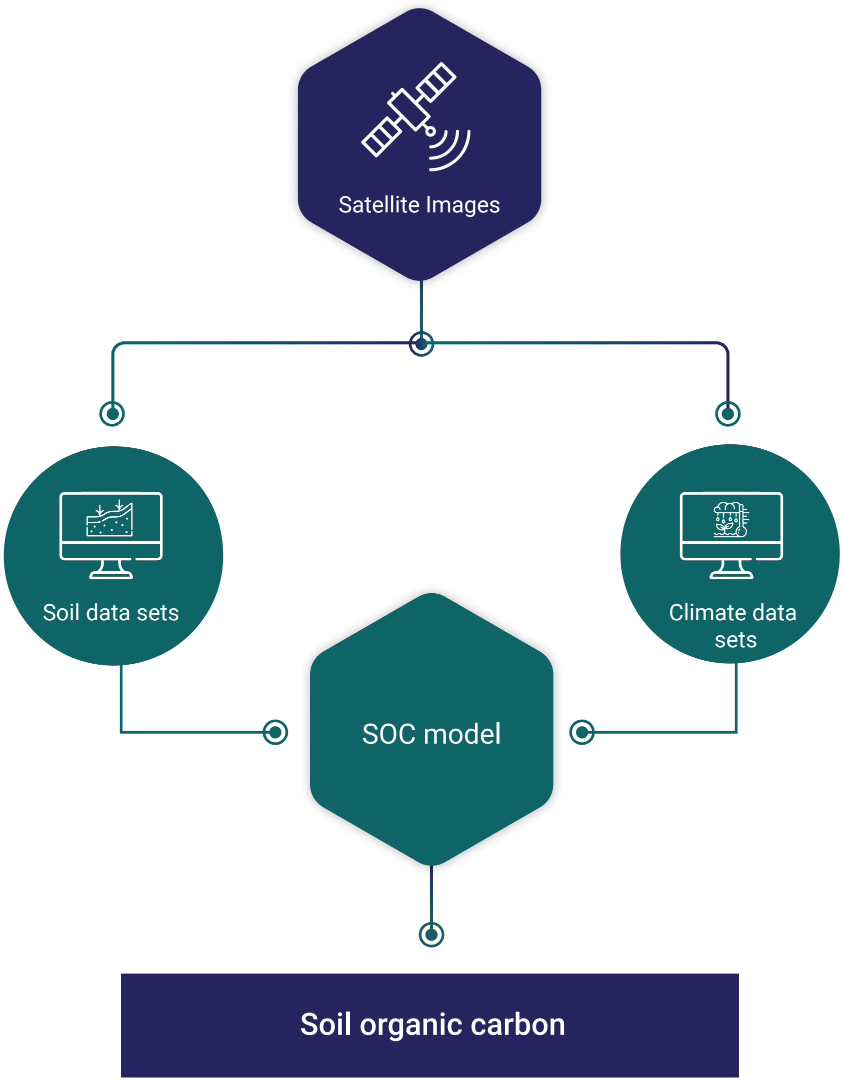


Figure -5: Steps showing the digital mapping and measuring of soil organic carbon

SatSure's Solution -Carbon Assessment of Agricultural Lands and Measurement of Carbon Credits

SatSure aims at generating additional revenue streams for farmers through carbon credits. The SatSure solution also aims at helping farmers protect and nurture their resources through sustainable farming (figure-6).

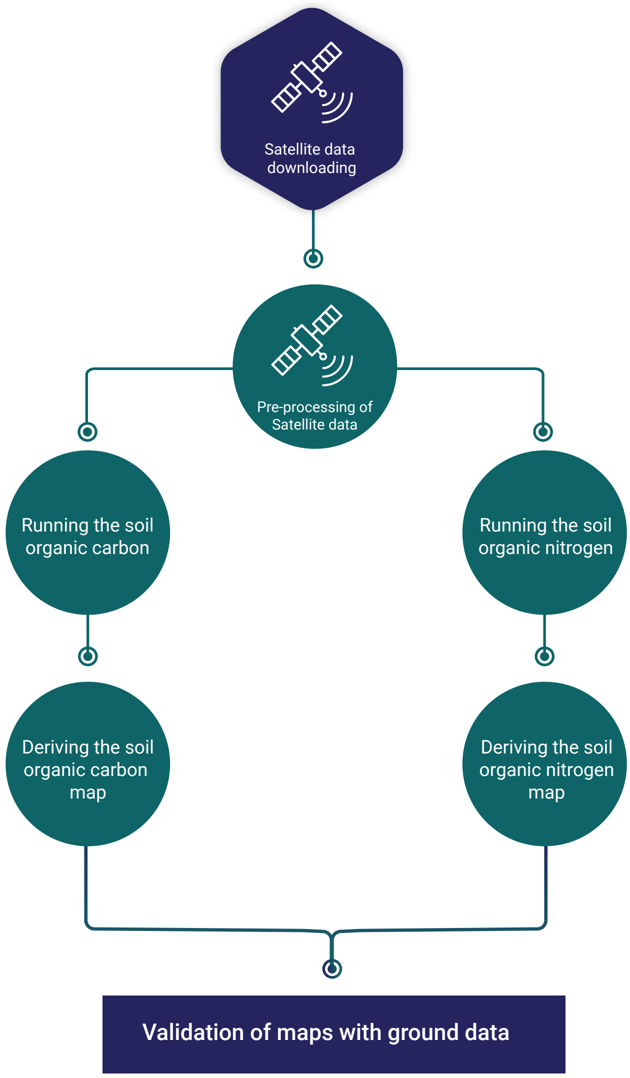


Figure -6: Step for estimation of soil organic carbon & nitrogen

Additionally, this initiative would support the climate sustainability agenda by improving the soil sequestration capability of agricultural land. As part of the proposed working model, SatSure uses digital soil mapping to qualitatively assess the degree of soil degradation in agricultural landscapes by categorising the degradation into severity classes (Chikhaoui et al., 2005) and to quantitatively predict SOC concentrations (Chen et al., 2000; Gomez et al., 2008; Frazier and Cheng, 1989; Rossel et al., 2006). Spectrographic analysis to digitally map soil characteristics has been used in precision agriculture because rapid, field-scale assessments of soil properties allow farmers to efficiently identify and treat soils in which nutrients are limited (Mulla, 2013).

Linear regression models developed from laboratory hyperspectral reflectance and chemical measurements of soil samples have often been used to calibrate spectral indices for predicting soil properties based on soil colour (Bachofer et al., 2015; Ben-Dor and Banin, 1995; Frazier and Cheng, 1989; Gomez et al., 2008; Mulder et al., 2011; Nanni and Demattê, 2006).

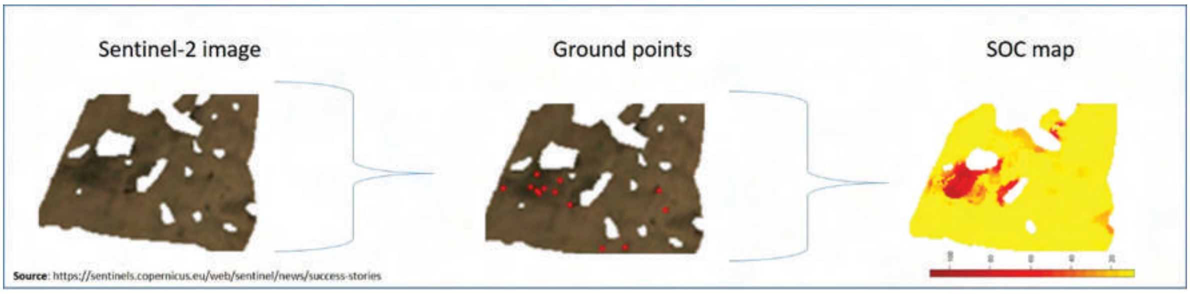
Soil colour often varies due to SOC and soil moisture (Escadafal, 1993; Schulze et al., 1993). Soils with higher SOC concentrations are typically darker coloured and have lower spectral reflectance than soils with lower SOC content (Rossel et al., 2006). Similarly, increasing soil moisture causes soil to appear darker because the reflectance of incident radiation in the visible spectrum uniformly decreases with rising water (Nocita et al., 2013; Weidong et al., 2002).

However, unlike reflectance changes due to SOC contents, the uniform decrease in reflectance across the visible wavelengths with increasing soil moisture indicates that the use of band ratios can remove the impact of soil moisture on spectral reflectance (Nocita et al., 2013; Stoner and Baumgardner, 1981).

Technology Overview

i. SatSure uses the reflectance at 478, 546, and 659 nm for blue, green, and red, respectively, which correspond to the centre wavelengths of the Sentinel-2/ hyperspectral sensor.

ii. Use universal indices for mapping the surface SOC (Thaler et al. 2019; Gitelson et al. 2003; Rodriguez et al. 2006; Sims & Gamon 2002).



iii. Use 10m/ 30m pixel resolution Sentinel-2/ hyperspectral satellite image.

iv. Within the field, we collect the soil samples to a depth of 15/ 30 cm (Liet al., 2018). The samples are sieved to <2 mm and ground to a powder, and the depth-averaged SOC concentrations for the 15/ 30- cm profile is measured (Li et al., 2018). We use the spectra radiometer, and the field surface spectra are collected.

v. The Sentinel-2/ hyperspectral images were acquired for the time when the field was ploughed and lacked both crop residue and crop cover.

vi. We use the SOCI to predict SOC within the field following the method, i.e., using a subset of the measurements from the field to locally calibrate a relationship between the SOCI and SOC and then use the local calibration to predict measured SOC values.

vii. SatSure's soil moisture product is used to know the correlation between both and understand the distribution of surface organic carbon.

vii. The distribution of surface carbon is checked with respect to slope, aspect, runoff, DEM, soil type, crop type, irrigation etc. and regenerative carbon potential is measured in near real-time.

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About SatSure

SatSure is a decision analytics company leveraging advances in satellite remote sensing, artificial intelligence, and cloud computing to answer large area questions for SDGs of financial inclusion, food security, sustainable infrastructure, and climate action.
Over the last four years, SatSure has worked across India, SEA, MEA and Europe with Government, multilateral and private organizations monitoring more than a million sq. km per week. SatSure has been recognized globally for its work by MIT, World Bank, ADB to name a few, recently becoming a part of the World Economic Forum's Global Innovators Community.