

A Comparative Appraisal on Satellite Remote Sensing Data as a Utilitarian Tool in Forest Health and Fragmentation Analysis

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ABSTRACT: The health of the forest vegetation is one of the driving factors and indicator of climate change impacts. Fragmentation of the forests on the other hand brings out the implications of the various stressing factors on the spatial extent of the forests especially the increasing population and industrialization, which has always impacted the forested regions in the form of deforestation for commercial purposes and conversion of forest land for cultivation. Hence there is a demand for spatial assessment and continuous monitoring of the forested regions. With a wide range of advancing technologies, remote sensing methods are increasingly being employed for monitoring a number of remotely measurable properties of different types of vegetation. This paper reviews the utilitarian application of remote sensing as a tool to assess the health of the forest regions. The various multispectral satellite image derived vegetation indices like Broadband and narrowband Greenness, leaf pigments, canopy water content and Light use efficiency can be used as a combined tool to generate a comprehensive health metrics for the forest canopy. These new indices may be useful in remote sensing plant physiology status as well. Various band ratio exist for above factors depending on the bands available in the selected dataset. A detailed discussion of the existing multispectral satellite sensors capable of studying the forest canopy is presented herewith, in addition to briefing on the potential of the latest microwave remote sensing technique for vegetation studies. The estimated vegetation indices can be used to generate the final health map of forest regions. Any change in the spatial extent of the forested areas and their pathway for future change can be assessed by the fragmentation analysis. The application of the discussed techniques in various environmental conditions are elaborated and the constraints in addition to the requirements for effective forest health monitoring is provided in this review.

KEYWORDS: Forest Health, Forest Fragmentation, Multispectral, Hyperspectral, Microwave Data.

I. INTRODUCTION

Forest health is a condition where in a forest has resilience capability, while meeting the present and future need of people at desired levels of values, uses, products, ecological service [11]. Remote sensing has been employed in measuring forest relevant data such as tree mortality rates, changes in crown density, detect damage extent in forest ecozones, changes in forest volume or mass, changes in stem density, standing volume etc. These data along with other biophysical parameters such as Diameter at Breast Height (DBH), Leaf Area Index (LAI) etc. have been used to assess forest health conditions of leaf loss, chlorophyll, foliar nutrients and identification of trees having root diseases. Canopy Chlorophyll Mass per Area is the product of foliar mass and chlorophyll concentration, which plays a vital role in assessing forest damage. Forests provide important ecosystem services, such as carbon sequestration, habitat for species that contribute to maintaining biodiversity, mitigating climate change and the ability to filter and maintain water resources by Nemani et al [49]. However, forests are facing numerous threats and stress factors such as

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deforestation, drought, climate change, invasive species, susceptibility to pests and pathogens, air pollution, disturbance-induced mortality from fire, water or wind, land-use changes or unsustainable management. The conservation and improvement of key forest functions is therefore imperative, as healthy vegetations are more stable and resilient to various stress types, disturbance and resource limitations.

Forest fragmentation is the process through which formerly large and continuous extensions of forests turn into a set of small and isolated patches [24]. The harmful consequences of forest fragmentation for certain species derive from three main causes: reduction of the size (area) of the remaining forest patches, increased isolation of the fragments, loss of overall connectivity, increased edge effect and disturbances from the surroundings. For these reasons, fragmentation indices can serve as spatial indicators for assessing whether critical components and functions of forests are being maintained [59].

The framework of this paper appends the discussion of the Forest health and fragmentation techniques including both multispectral as well as microwave satellite datasets for each entity which has been dealt in detail.

II. FOREST HEALTH

Forest health analysis using satellite image processing techniques has been used in various applications of vegetation and landscape classification, biomass mapping, invasive plants detection, fire fuel mapping and canopy or foliar water stress, fire detection and progression mapping, post fire burn area and severity mapping, and insect infestation detection etc. Major remote sensing studies are equipped with assessing spectral signatures or simple indices (calculated from reflectance data) such as the Normalized Difference Vegetation Index (NDVI) for forest health analysis. Very few studies have been attempted for remote sensing of absolute forest water stress and biomass growth using physiological and physical algorithms. Former studies estimated biomass by NDVI or other simple indices using correlation and regression methods, which may not be applicable in dynamic environmental conditions [19].

a) MULTISPECTRAL MODE

An index is the combination of spectral bands available in the satellite data, which is then mathematically operated to form a single index value [11]. For regression or other data analysis, spectral indices and data transformations were used for pre-processing. Accuracy of the physical characteristic observed by the satellite data is determined by regression analysis. Normalized Difference Vegetation Index is widely used based on availability of IR and NIR bands in the dataset [56]. NDVI was a major tool meant for parameters such as fuel mapping, foliar moisture stress detection, burn severity mapping, vegetation classification, forest type mapping, invasive weed detection and land degradation model as well. Foliar moisture indices are formulated with short wave infrared band and red band [67].

Normalized Burn Ratio (a band ratio of NIR and IR) is for burn detection and burn severity mapping [35]. Principal Component Analysis (PCA) and Tasseled Cap Transformation (TCT) are two data transformation methods to lower the coefficient of variation between indices and on-field observed data. The dataset was processed using PCA and TCT. The common methods used in fuel mapping are regression methods and gradient modelling. Gradient modelling refers to modelling of natural phenomena occurrence by the use of environmental components (topographical, biogeochemical, biophysical, and vegetational). This approach has been used with moderate success in estimating fuel types and fuel loading [67]. All the four categories of vegetation indices and spectral transformations are inputs to regression equations or gradient models. The accuracy of fuel mapping is almost 50% to 85% by using PCA and TCT analysis.

Landsat, ASTER, and SPOT were governed for foliar moisture prediction by regression methods [13]. The inputs were the components of TCT, PCA, vegetation indices, or foliar moisture indices. The R^2 values ranged from 0.5 to 0.8. For regular analysis, TCT wetness parameter is suitable for estimating foliar moisture [67]. Vegetation and landscape mapping used classification algorithms, both supervised and unsupervised [32] and Regression-tree classification procedure as well. The classification software packages of eCognition (Definiens Inc., Boston, MA,

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USA), Feature Analyst (Visual Learning System, Inc., Missoula, MT), ERDAS Imagine (Geosystems Geospatial Imaging, LLC, Norcross, GA, USA) have been commonly used for vegetation classification and mapping [57]. Satellite derived vegetation indices such as NDVI can monitor vegetation vigour. High percentages of spectral variance of individual scenes can be explained using TCT, as the TCT greenness and wetness bands have strong correlation to the percentage of vegetation cover [16]. The greenness corresponds to density of green vegetation while the wetness feature measures soil moisture content [16].

Beck and Gessler [8] proposed methods for mapping and monitoring forest status through the creation of departure maps from average NDVI, TCT greenness and wetness index derived from an expanding time-series of Landsat imagery. The departure classification used clearly delineated built-up features within the negative departure from average class. Forest water stress (foliar moisture) were determined using regression equations from inputs of vegetation and moisture indices or PCA and TCT transformed data [13] [67]. Regression equations may produce errors for different locations and environmental conditions. The difficulty in mapping forest water stress and biomass growth is to correct the effects from mountain elevation, slope and aspect which cause surface temperature and radiation variations and can result in errors using energy balance methods by Morse et al., [47].

Vegetation indices are commonly used to quantify vegetation cover, vigour and density in remote sensing. The Normalised Difference Vegetation Index (NDVI), which distinguishes actively growing vegetation from background features, is the most widely used vegetation index in remote sensing studies Hansen et al., [26]. Other indices for measuring cover commonly used include, the Soil Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), Modified Soil Adjusted Vegetation Index (MSAVI) and the Transformed Soil Adjusted Vegetation Index (TSAVI) by Qi et al., [54]. Measures of plant regeneration can be well-versed by changes in land cover through change detection analysis including increases in cover by Lunetta et al., [42] and changes in canopy roughness as vegetation ages, however methods are not well developed. Studies of vegetation health using vegetation moisture [20], biochemical properties of plants including chlorophyll content by Coops et al., [15]; Houborg et al., [33], and other leaf pigments were also conducted in Australian Brushland. Primary productivity, Lignin and nitrogen content were measured using remote sensing to in ecosystem functioning [43]. They had employed chlorophyll fluorescence imaging to detect stress in vegetation, which is a pre-visual indicator of stress as well.

He et al., [29], measured physiological and structural indicators of water stress in vegetation in terms of wilting, canopy temperature and loss of leaf area by Bellvert et al., [9]. Tree mortality due to drought, wildfire and changes in management activity were detected using remote sensing methods as in Gillis et al., [22]. Two forms of methodologies were used to integrate site-based data and remote sensing data together. The most widely used approach involves the use of site-based data to characterise training sites and/or assess the accuracy of classifications from remote sensing analysis. The second approach uses site-based data to calibrate and validate remote sensing indices and measures, where the remote sensing variable is used to predict the same biophysical variable on the ground (e.g. percent cover and LAI). Coops et al., [14], assessed the linear relationships between LAI site-based data with NDVI and the SR (simple ratio) derived using Landsat MSS data, yielding R^2 values on 0.71 and 0.53 respectively. Sheffield [63] compared data from the site-based BioMetric method (Department of Environment Climate Change and Water, 2011) with multi-spectral remotely sensed data using linear regression and found that some vegetation cover and stem density measures showed reasonable correlation with the imagery (R^2 values 0.58 and 0.76 respectively). Overall site condition scores showed moderate correlation with the imagery, yielding an R^2 value of 0.55.

Leckie et al., [38] established the ability of multispectral imagery acquired with CASI to locate and assess trees infected by *Phellinusweirii*. Using classifications of healthy, light-healthy, light, moderate, severe, 100% needle loss, snag, and shadowed snag, accuracy was in the order of 55-60%. It was concluded that high resolution multispectral imagery combined with automated procedures appeared to be viable for detecting disease centres where severe symptoms were present.

Wehr et al., [71], involved eCognition Developer to segment a pan-sharpened WorldView-2 ortho-image that detected individual trees and tree clusters of ash (*Fraxinus excelsior*) suffering crown dieback. Several predictor variables that incorporated Red band, were derived from spectral library of WorldView-2. Subsequently, they performed supervised classification using a multiple logistic regression technique thereby mapping four different levels of damaged ash achieving an accuracy of 77%. Using colour-infrared imagery captured by an UAV, Lefsky et al. [40] applied the multi-resolution segmentation and object-based image analysis in eCognition Developer to classify an infestation in oak (*Quercus* sp.) stands by the oak splendour beetle (*Agrilusbiguttatus*). In addition, Lefsky et al.

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[40]also exemplified segmentation *P. radiata* crowns affected by *Fusarium sp.* using QuickBird dataset along with eCognition Developer software.

b) MICROWAVE MODE

The fusion of high spatial resolution data from optical and active sensors now permits the extraction of a mixture of spectral, textural and structural metrics that can be directly assigned to individual tree crowns, thereby enhancing the remotely sensed information that can be related to crown-level biochemical and biophysical attributes. Several forest health studies have highlighted the issue of pixels or segmented polygons (i.e. tree crowns) containing shadows or spectral information from non-targeted features. Bare soil and under-storey vegetation, for example, are often visible when viewed synoptically over dead and dying trees. A solution to this problem is the fusion of the spectral imagery with height information provided by LiDAR sensors or canopy height information derived from stereo-photogrammetry in combination with an accurate digital terrain model (DTM). Shendrkly et al.,[64], for example, used full-wave form airborne LiDAR data to detect individual *Eucalyptus camaldulensis* tree crowns in 3D occurring in a native forest suffering chronic drought. They then extracted hyperspectral data from the sunlit portions of each tree crown as well as attributing a series of LiDAR structural indices to each crown. The most important predictor variables were then applied to classify the health of individual trees using RF. They achieved an overall accuracy of 81% for classifying crown dieback and an overall accuracy of 70% for crown transparency parameters used to map the health of individual trees.

Sinha et al., [60], used approaches for forest biomass estimations on AGB over Queensland, Australia using backscatter values and interferometry technique, along with polarimetric analyses. Beaudoin et al. [7] testified that HH return was linked to both trunk and crown biomass while VV and HV backscatter returns with crown biomass. Longer wavelengths (L and P bands) with cross-polarizations (HV and VH) produced better result for biomass-related studies than short wavelengths (X and C bands) with co-polarizations (HH or VV) Le Toan et al.,[37]. The significant problem with this method is the saturation level of different wavelengths and polarizations relevant in several studies. The aspects on which the saturation levels depend are the wavelengths polarization,the vegetation stand structure and ground condition characteristics Ghasemi et al.,[21]. Santos et al. [58] indicated the use of the ratio between C and L or P band to solve the saturation problem. Ranson et al. [55] employed a synergic approach of forest succession and radar backscatter models to estimate forest biomass and examined reasonably good results. Landscape properties like topography, surface water and forest structure are beneficial for estimating forest biomass using SAR showing more accurate results by Austin et al.,[6]. The approach involving interferometry has the potential to overcome the saturation problem as it has a relatively high saturation point. In contrast, Pulliainen et al. [53] proposed that the accuracy of this technique was highly dependent on certain factors which inherit dynamic variation including the site conditions (wind speed, moisture, temperature, etc.). It was observed that the estimation accuracy can enhance while using multi-temporal SAR images acquired under favourable conditions. Pulse coherent SAR operating between 80–120 MHz can be used to measure heavy forest biomass Imhoff et al.,[34]. Luckman et al. [41] evaluated the accuracy for biomass estimation using the procedures of boreal, temperate and tropical forests, where the best result was achieved in boreal forests using L-band images with 1-day interval.

Hoffer, [11], observed that, in forested areas, trees with large crowns cause a rough texture on the radar imagery, as do stands having a very low canopy closure. Brushland areas of Thailand produce a finer texture. Thus, differentiation and mapping of major vegetative cover types can be achieved. Some agricultural crops can be accurately identified and mapped using SLAR imagery at selected times during the growing season by Morain and Simonett, [47]. Apart from the differences in canopy texture, variation in moisture content of vegetation has a significant prominence on Radar signal, particularly in shorter wavelength bands. This is because the radar signal at these frequencies is strongly reflected by material with a high dielectric constant, and the dielectric constant is closely correlated with the moisture content. Therefore, vegetation having a high moisture content, or a fairly complete canopy of turgid vegetation, will produce a relatively light tone on the radar imagery [47]. The ability of radar to discriminate between agricultural fields with different levels of moisture is one of the primary reasons that certain crop species can be identified at specific times during the growing season. It also offers some hope for detecting stress conditions. One of the characteristics of radar which has often been misrepresented is its ability to 'see through' vegetative canopies. Longer wavelength systems, such as L-band, do have a significant potential for penetrating surficial cover, but the shorter wavelength systems, such as K-band, do not by Mathews et al., [8]. Since the spatial resolution of L-band radar

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is much poorer than that of the shorter wavelength K- or X-band systems, and since it has been primarily the K- or X-band systems that have been available to scientists for vegetation mapping, most of the data obtained thus far has come from K- or X-band systems. With these systems, in situations where the terrain does not cause significant variations, the geometric characteristics and moisture content of the vegetation itself are the dominant factors influencing the texture and tone of the radar image [47]. The polarization of the radar signal can also influence significantly, the appearance of different vegetative types on radar imagery. In some cases the HH polarization gives better differentiation between vegetative cover types than the HV; in other cases the reverse is true as in Weismiller et al., [73].

The primary characteristic that makes LiDAR well suited for applications to monitor forest health is the potential to reconstruct 3D forest structures within and below the canopy, which cannot be provided by passive remote-sensing techniques. The vertical forest structure is of high relevance for the description of forest heterogeneity and for biodiversity assessments [20]. The most important environmental application of LiDAR is the precise mapping of terrain and surface/canopy elevations. Such digital terrain models (DTMs) or digital surface models (DSMs) can be useful in monitoring FH indicators such as changes in tree height resulting from damage or deviations in growth due to stress. A widely used LiDAR metric to represent vertical canopy complexity is the coefficient of variation. Higher values correspond to more diverse multi-layer stands, while low values represent single layer stands as in Muller et al., [50]. The coefficient of variation can be applied to the point clouds, the digital crown model or individual trees. Heurich and Kennel, [30] applied this principle and classified forest stands according to stand structure with LiDAR data and achieved an overall accuracy of 97%. Another approach is the partitioning of the vertical structure into different height layers in relation to ecological importance. Latifi et al., [37] divided the canopy into height layers according to phytosociological standards and found a strong relationship with different LiDAR metrics using regression models. Similar approaches were used by Vogler et al., [70] and Ewald et al., [17] to represent the understory relevant for birds and deer and to detect forest regeneration. A more recent study applied a 3D segmentation algorithm to estimate regeneration cover and achieved an accuracy of 70% as in Ole et al., [52]. LiDAR-derived information about the vertical structure is also used for the assessment of forest fuels and their vertical distribution, which are important input variables in forest fire models supporting fire management.

Alireza et al., [20] analyzed ALOS PALSAR data which was acquired during the dry season to minimize any influence of varying rainfall and soil moisture. The incidence angle and pixel spacing of this image were 30 m and 23.1° respectively. Multi-polarization SAR images are composed of four types of polarimetric images represented by scattering matrices. For each polarimetric channel, the statistics is like a single polarized image as in Gonzalez et al., [23]. Therefore, studying statistical model of single polarized SAR can be extended to describe more polarized channel. To define statistical models of a SAR image, different levels (in terms of scattering) are divided into homogeneous, heterogeneous and highly homogeneous groups. Homogeneous group refers to an environment with moderate or poor backscattering. For example, smooth surfaces, slack water, and road have poor backscattering. Also, crops and rough surfaces have medium backscattering. Heterogeneous environment refers to targets like forests. Highly heterogeneous environment is known with strong backscattering as manmade objects, urban areas and steep slopes of the terrain. Synthetic aperture radar acquires the backscatters from the target as amplitude and phase. In the intensity images, speckle is multiplicative with original signal as in Lee et al., [40]. Some studies have used the logarithmic function to convert the multiplicative model to additive model and using the desired algorithm as in Yusheng et al., [75]. The main drawback in applying this technique is that the dynamic range of the original image is compressed by the logarithm operation [40]. Independent Component Analysis (ICA) is a statistical method for transporting observed multidimensional random vector to the mutually independent components. Compared with other methods based on second order statistics, ICA not only can eliminate the first and second order correlation, but also can remove the high-order correlation data to obtain the independent components as in Wang et al., [72].

Castillo et al., [6] accomplished an area-based mapping of defoliated pine stands using LiDAR. The method bestowed in this study appends mapping of the defoliated forest stands based on a two-stage procedure using LiDAR and field plots. LiDAR returns that are reflected from the canopy were used to calculate features that were used in the needle loss prediction. Since LiDAR pulse penetration can be effected by Forest canopy cover (FCC), thus it is to be considered in area-based predictions of defoliation in forest environment. In this study, within plot FCC is first determined, with LiDAR features calculated only from that particular area (*i.e.*, uses only the LiDAR returns that are reflected from within the forest canopy). Factors such as overlapping branches from neighbouring trees and understory

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vegetation hinders defoliation prediction. To minimize the effect of these factors, only LiDAR returns reflected above mean plot height are used. The mean height estimate is calculated as 50% of the maximum LiDAR height. Additionally, in the boreal forest environment of this study, tree crowns above this mean height designation typically do not overlap. In addition, with regards to understory vegetation or suppressed trees, such as understory spruces, are found below this level (although understory is only of slight concern in this study area due to the dominance of Scots pine). 84.3% is obtainable mapping accuracy, using proportions of canopy returns below 80% and 90% relative heights for two important defoliation classes by using the foresaid approach. It was also claimed that the mapping accuracy was not overly sensitive to LiDAR pulse density. The method and information outcomes could be linked to operational forest management planning practices.

III. FOREST FRAGMENTATION

Deforestation and fragmentation are perspicuous but related phenomena. Forest loss is simply the conversion of forestland to some other land use, but forest fragmentation occurs when a large region of forest is broken down, or fragmented, into a collection of smaller patches of forest habitat. Forest landscapes are at high risk of forest fragmentation because of changes in land cover due to processes such as agricultural intensification, logging and infrastructure development. These changes have led not only to the loss of habitat and biodiversity, but also to the modification of natural landscapes and ecosystem functions. Non-anthropogenic drivers such as natural hazards also contribute to forest fragmentation, especially in mountain regions. However, very few studies have been conducted to understand the correlation between natural hazards and forest fragmentation. Therefore, understanding the link between natural hazards and forest fragmentation at different scales is also important for implementing conservation strategies for proper land management in mountain regions.

a) MULTISPECTRAL MODE

Amit et al.[3] assessed Landsat images for the years 1976, 1998 and 2014, using supervised classification with the maximum likelihood method. The land cover maps were then analysed to understand the changes in land-use and land-cover, using the cross-tabulation module detection method in GIS. Finally, all land cover maps were converted to forest and non-forest areas to detect forest fragmentation areas, using the landscape fragmentation tool (LFT v2.0). Therefore, the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH®) model was applied to improve radiometric and atmospheric correction. The FLAASH model technique was applied for handling particularly stressing atmospheric conditions. The images were matched with geo-referenced OLI images by means of image-to-image matching method. All images were presampled using nearest neighbour technique, root mean square error of less than ± 0.5 pixel per image to a 30 m resolution. In addition unsupervised classification was also applied before the supervised classification to aid in the identification of dominant land-cover types and improves the classification accuracy. Then, supervised classifications using the maximum likelihood method were performed for the 1976, 1998, and 2014 Landsat images. For each class, 20 ground-truth polygons were digitized. A cross-tabulation module detection method was used to detect land-use and land-cover change, through which a LULC change matrix was produced. This matrix provides essential information about the nature and spatial distribution of land use changes. A change matrix enables the main types of changes or directions in the study area. Then, the change in LULC was analysed to depict gains and losses for the two time periods. The change matrices of the 1st period (1976–1998) and the 2nd period (1998–2014) were also used to drive the gains and losses for land-cover categories. The gains for each class were derived by subtracting the persistence from the column total, and the losses were computed by subtracting the persistence from the row total.

Aditya et al., [1] evaluated Land use Land cover changes of Shendurney Wildlife Sanctuary, Western Ghats using Landsat 7(ETM +SLC) and Landsat 8(OLI/TIRS) using ancillary data from Soil Toposheets of 1:50000 scale and Google Earth Images. The reflectance of datasets were corrected and unsupervised classification with seven classes such as waterbody, evergreen, semi-evergreen, deciduous forest, mixed jungle, grassland and barren land were used as Land use/Landcover classification. The classified dataset were further processed and the result of the study revealed that there was an abrupt shrinkage in extent of deciduous and mixed forest, whereas there was an increase in water body due to Kallada dam construction in the vicinity of the Sanctuary. It was considered that land use changes were highly scrutinized in transition zone and areas close to settlements as well.

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Anita et al., [5] analysed data from summer 2013 and 2014 were radiometrically and atmospherically corrected using FLAASH, a module embedded in ENVI software. FLAASH corrects wavelengths in the visible through near-infrared and shortwave infrared regions, up to 3 μm . The module created a cloud map classification image used during FLAASH processing to refine the calculations. Mid-Latitude Summer (MLS) atmospheric model was used to run the corrections. The histogram equalization was applied to avoid any differences in radiometric scheme of different images. Instantaneous NDVI was calculated for each image and the simple image NDVI difference approach was used to detect the forest damage. The images were chosen in the peak of growing seasons when any changes in NDVI are most prominent. Using the ENVI image change flow approach the NDVI difference image was generated. The default threshold was applied to generate the NDVI difference image between 2013 and 2014. The change detection areas were delineated based on the NDVI default value of zero for change-no change areas. The ground truth polygons were based on the damage intensity of forest stands in accordance with the Methodology for Damage Assessment Caused by Natural disasters, Croatia. The forest units were separated in broadleaf and coniferous forests although many units consisted of mixed forest represented by both broadleaf and coniferous stands. Each forest type was ranked based on the impairment intensity and was classified as destroyed or damaged at various levels, using percentages.

Steven et al., [67], used subtraction of TM wetness index from preceding dated Landsat 8 images to emphasize forest difference of interest. Thresholds were applied based on field Knowledge of disturbed areas. The available forest inventoried GIS data were used to mask all non-forest areas from change detection procedure. The Threshold of wetness differences were used to develop a map. The landcover map were produced based on a decision –tree-classifier, a unique combination of supervised and unsupervised classification that rely on spectral, DEM and polygonal GIS data to extract the maximum information from mapping assembled database. K-means unsupervised classification was used to separate forested and non forested areas, an empirical slope decision rule separated lakes and shadows, an empirical elevation decision rule separates shadow and close conifer stands at lower elevation, empirical slope decision rule separated slope and wetland classes based on distances to road and stream and empirical GIS overlay decision rule were used to embed cultural features, forest harvest polygons and to merge classes which are spectrally indistinguishable based on Bhattacharya Distance measures. Accuracy assessment of resultant land cover classification map was based on digital orthophotography and random sample of 494 locations.

Molinario et al., [47] created a forest fragmentation map using a GIS model and the Landscape Fragmentation Tool (LFT) Parent et al., [54] based on research by Vogt et al., [71]. An edge distance parameter was applied to the input dataset and used to perform separation and inclusion operations between patches of forest and non-forest, resulting in a nuanced forest fragmentation-specific classification. The expansion of the rural complex and isolated forest perforations can degrade the forest through forest fragmentation, resulting in formerly intact forest ecosystems being impacted by edge effects created by clearings. Edge effects are pervasive processes in tropical forests that can lead to challenges in forest ecology and habitat fragmentation as well as increasing access to interior forest. The width of edges and the specific characteristics of edge effects depend on the ecology of the forest, local environmental variables, the abruptness of the edge and its temporal permanence as in Harper et al., [18]. Most effects occur close to the forest/non-forest boundary and decrease in frequency and severity with distance Broadbent et al., [10].

Paramesha et al. [53] executed change analysis of Biligiri Rangaswamy Temple Tiger Reserve, in the Western Ghats, by using satellite images of 1973, 2001 and 2014. All images used for analysis were selected from the dry season to reduce scene-to-scene variation, which may possibly occur due to sun angle, soil moisture, atmospheric condition and vegetation phenology differences. In addition to these, the change in the NDVI was most noticeable only during the dry season, and also cloud cover was more pronounced in the images of other seasons, which may potentially affect the change analysis process and real change in NDVI. Overall, in this method an attempt was made to improve the conventional NDVI differencing technique of identifying change trends by applying thresholds and computing quartiles to further classify the greening and browning areas as low, medium and high change categories.

Haines-Young et al., [27] employed a set of five forest maps at WiFS resolution for each quadrant and pinned that upscaling procedure was more adequate for estimating actual fragmentation at coarser scales, considering a wide set of 10 spatial indices that are being commonly used to characterize landscape patterns fragmentation. These indices are regarded as forest fragmentation indices because they are all sensitive to the breaking apart (dissection) of forests. All the indices were computed at the class level in categorical (classified) forest data via Fragstats software, considering the 8-neighborhood rule for the definition of the forest patches. For each of the indices landscape metrics such as-Number of patches, Mean patch size, Largest patch index (LPI), Mean radius of gyration (RG), Edge length

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(EL), Mean nearest neighbour distance (NN), Clumpiness index (CI), Patch cohesion (PC) index, Landscape division (LD), Aggregation index (AI) were derived. They have experimentally found that the variations of several fragmentation-related indices with spatial resolution can be described through scaling power laws Wu et al. [73] the three very common fragmentation indices being (Number Of Patches, Mean Patch Size and Edge Length) for which power scaling laws have been reported consistently among different authors and study areas.

b) MICROWAVE MODE

Haile and Allan, [25], examined land cover classification and analysis using radar and Landsat data of North central Ethiopia. De-speckling and texture measures using different window sizes were applied to the original radar data. Maximum likelihood classifier and C4.5 decision tree techniques were used to classify both Landsat and radar data. WEKA, open source software, was used to apply a decision tree for the classification. The analysis focused on the impact of radar data enhancement methods on classification accuracy assessments. The de-speckling techniques used in the study were Median, Lee-Sigma and Gamma-MAP. Lee-Sigma assumes normal distribution and both mean and variance are used to estimate the value of the particular pixel. However, Gamma-MAP filter assumes non Gaussian distribution and it considers statistical and geometrical characteristics of the pixels. During accuracy assessment, the original radar image without any enhancement methods produced poor classification accuracy results for each class and overall classification. Lee-sigma, Gamma Map and Median de-speckling techniques improved the overall classification accuracy by about 15, 18 and 20% respectively at window size 27. This shows overall accuracy improvement to more than 81% by using de-speckling. Increasing the window size beyond 27 by 27 did not increase the overall accuracy result. Adding raw radar data to Landsat data also produced 3% overall classification accuracy improvement.

Angela et al., [4] modelled above ground biomass (AGB) in a similar manner to visible-near infrared reflectance-based indices, the SAR backscatter-AGB relationship is curvilinear and many studies have found that it typically saturates in the range of 100–150 t/ha, whereas others have found lower thresholds of saturation. Thus, biomass and biomass loss are difficult to model and estimate using backscatter or backscatter-based indices in dense forests. Studies in forests below the saturation threshold have been successful, however. It include explicit estimation of AGB loss as well as studies that only estimated biomass for a single date, but that have potential for temporal or spatial application to estimate biomass loss. Other examples are given for leaf area index (LAI), canopy height and forest density that have potential for canopy degradation mapping. With the BIOMASS mission of ESA planning a polarimetric and interferometric P-band satellite sensor and NISAR (NASA-ISRO Synthetic Aperture Radar) mission for 2020, the combined use of these three SAR features (polarimetry, InSAR, long wavelength) will be the most obtainable method for temporal monitoring of forest anatomical condition and degradation. It is clear that forest removal, disturbance and degradation analysis and monitoring using RADAR depends on structural forest change that is manifested as a consequence of a given source of stress or degradation. A direct analysis of backscatter response in specific polarizations and wavelengths, or combinations of these, has been the most common approach and has shown some success. However, more recently, improved potential has been shown using multi temporal data, InSAR, polarimetric and decomposition techniques to detect and estimate changes in signal polarization, phase, and volume, surface and double bounce scattering contributions that are related to changes in canopy structure Le Taon et al., [38]. It is in these areas that FH change research using RADAR data needs continued efforts.

IV. CONCLUSION

Forest biomass assessment involves the volumetric analysis of the vegetation and this exploits the intrinsic capability of penetration of Microwave sensor through the tree canopies which is completely absent in optical remote sensing. The estimation is also sensitive to wave polarization and frequency, as higher wavelengths have greater penetration capacity and cross-polarization waves are more sensitive to biomass. The analysis also varies according to the moisture content of the vegetation. These unique qualities of Microwave sensor provide better estimation of biomass with reduced uncertainties in the assessment, as microwaves saturates at higher levels of biomass in comparison to optical electromagnetic waves. In spite of such high potentials, there are some drawbacks of using Microwave sensor that needs to be overcome. Compared to optical data, the x- and y-resolutions are not same as range resolution varies with local incident angle. Interpretation requires good understanding of microwave frequency

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interaction with various targets, as data interpretation is affected by occurrence speckles and image distortions such as overlay, foreshortening and shadows; due to undulating terrains.

On the contrary, some of the worth mentioning aspects of multispectral sensors is their obligatory provision of large quantum of datasets with better spatial resolution and easier data processing compared to microwaves. Cloud cover can hamper image collection. Spatial resolution of above 20m forms a major interference for supervised classification. Availability of 3-10 bands with wider spectral band width makes it insensitive to the finer spectral signatures, wherein hyperspectral satellite data with narrow spectral band width is capable of bringing out finer canopy information. Absence of deeper penetration power makes it unfit for forest taxonomic studies. Revisit time of multispectral sensors ranges 10-15 days, becoming a hurdle of quantifying data in the interval time. However, for multispectral sensors, the fore said constraints may be fixed to a limited extent such as by means of deploying pan-sharpening yielding a high resolution color product.

At length it can be construed that, synchronisation of optical and microwave satellite data improves ability to detect and identify objects target features by analysing their respective spectral signatures. Fusion of multispectral and microwave sensors can be a viable option for frequent updates due to better revisit frequency. A constellation of microwave and optical sensors advances cloud free acquisition potential, thereby minimizing collection period and facilitating observance of acquisition window. Such a type integration enables users to select best satellite solution and its implementation as easily as possible based on user's area of interest, its temporal constraints and hurdles that may come into light.

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