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Abstract. The quantification, mapping and monitoring of biomass are now central issues due to the importance of biomass as a renewable energy source in many countries of the world. The estimation of biomass is a challenging task, especially in areas with complex stands and varying environmental conditions, and requires accurate and consistent measurement methods. To efficiently and effectively use biomass as a renewable energy source, it is important to have detailed knowledge of its distribution, abundance, and quality. Remote sensing offers the technology to enable rapid assessment of biomass over large areas relatively quickly and at a low cost. This paper provides a comprehensive review of biomass assessment techniques using remote sensing in different environments and using different sensing techniques. It covers forests, savannah, and grasslands/rangelands, and for each of these environments, reviews key work that has been undertaken and compares the techniques that have been the most successful. © *The Authors. Published by SPIE under a Creative Commons Attribution 3.0 Unported License. Distribution or reproduction of this work in whole or in part requires full attribution of the original publication, including its DOI.* [DOI: 10.1117/1.JRS.9.097696]

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1 Introduction

Lignocellulosic biomass or plant dry matter (biomass) is a highly abundant renewable energy resource that can be used to generate a continuous supply of heat and electricity as well as solid, liquid, and gaseous fuels.[1] Therefore, plant biomass plays an important role in the global quest for sustainable energy solutions since it is a renewable energy source that is easily available to humans. Although it is considered that all fossil fuels such as coal and oil originated from buried living material, they are usually excluded from the definition of biomass. Biomass has stored energy through the process of photosynthesis. It exists in one form as plants and may be transferred through the food chain to animal bodies and their wastes, all of which can be converted to energy through processes such as combustion. Biomass has been converted by partial pyrolysis to charcoal for thousands of years. Charcoal, in turn, has been used for forging metals and for light industry for hundreds of years. Both wood and charcoal formed part of the backbone of the early industrial revolution prior to the discovery of coal for energy. Wood is still used extensively for energy in both household situations and in industry, particularly in the timber, paper, pulp, and other forestry-related industries. The easiest and most efficient way to use biomass as energy is through burning. When it is burned, a part of the internal chemical energy converts to heat. Biomass can also be burned in special plants called waste-to-energy plants which use the heat energy to create steam, which is then used to either heat buildings or create electricity.

The main benefit of biomass is that it is a renewable fuel. Not only does this give us a renewable source of energy to heat our homes, power our vehicles, and produce electricity, but it also helps us to utilize discarded waste that is filling up large dump sites. Many Asian countries are looking to biomass power plants to increase domestic energy outputs and reduce reliance on foreign energy supplies. Asia is expected to construct about 1000 MW of biomass energy capacity annually by 2020—twice as much as is expected in Europe.[2] Thailand, Indonesia, Malaysia,

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and the Philippines all have introduced feed-in tariffs to encourage biomass energy production.[3] Also, due to Asian climates, many countries can produce sufficient amounts of biomass.

Many countries of the world are now expanding resources toward quantifying, mapping and monitoring biomass due to its importance as a renewable energy source. However, biomass resources are distributed over wide geographical areas and their biochemical properties are highly variable over space. Furthermore, its suitability as a renewable resource is also site-specific. This makes biomass estimation a challenging task, especially in areas with complex forest stand structures and environmental conditions,[3] and requires accurate and consistent measurement methods.[4] Traditionally, two methods are available for the determination of biomass.[5] The first method is destructive sampling, which involves the complete harvesting of plots and subsequent extrapolation to a unit area of hectare.[6] The second method is based on allometry where allometric equations are used to extrapolate both *in situ* and remotely sampled data to a larger area to derive biomass and canopy volume from an easily measured attribute such as diameter at breast height (DBH), tree height, etc. Allometric relationships are used for estimating tree allometry which establishes quantitative relations between some key tree characteristic such as dimensions of trees (easy to measure) and other properties (which are difficult to assess). Both these traditional methods are accurate but are extremely time-consuming, costly, and generally limited to small areas and small tree sample sizes.[7–9] Moreover, extending this method to map forest biomass across a large area is extremely challenging when factors such as ecological differences, variations in inventory systems, and scattered sources of biomass data are considered. In addition, since the allometric coefficients are site and species specific and are based on a certain range of tree diameters, the use of standard allometric equations can lead to significant errors in vegetation biomass estimations if used outside the area where they were originally produced.[10] There have been efforts in developing generalized regional and national tree biomass equations that could be applied to a larger geographic footprint than most existing allometric equations.[11,12]

Another vegetation type of great interest is the tropical savanna, not only for the large regions it covers but also for the high interannual biomass dynamics. Grasslands and rangelands also have considerable biomass and thus energy generation capacities, especially since they cover around 40% of the earth's land surface. Remote sensing can be used to ascertain the potential availability of biomass over large regions and also to estimate biomass energy potential for different land-cover classes.[13] However, the actual recovery of this biomass will depend on the availability of technology to collect and utilize this material in an economical fashion.[14] Remote sensing techniques can be used in combination with geographical information systems (GIS) to evaluate the feasibility of such initiatives. These techniques can be used to evaluate the feasibility of and optimization of the locations of new biomass power plants[13] to evaluate the cost effectiveness of energy production from biomass[1] and to devise a framework for estimating residual biomass using satellite imagery and forest inventory data.[15]

Additionally, remote sensing is the best approach to estimate biomass at a regional level where field data are scarce or difficult to collect. Almost two decades have passed since pioneers such as Refs. 16 and 17 related biomass to reflectance recorded at the sensor. Since then, many studies in different regions have found strong correlations between biomass and reflectance at different wavelengths. In this paper, we review various techniques and platforms for biomass estimation. We look at forests, savanna, and grasslands/rangelands separately as each has its own characteristics and problems when it comes to biomass estimation. There have been several review papers on biomass estimation in the past few years; however, most of them have described remote sensing based estimation for forest biomass.[3,18–20] This current review incorporates remote sensing-based biomass estimation for three major vegetation ecosystems: forest, grassland and rangelands, and tropical savanna, that cover ~80% of earth's vegetative cover.[21,22] These vegetative surfaces on earth are more "natural" ecosystems without much human disturbance, unlike agricultural lands which are heavily dependent on cropping management, and thus provide an opportunity to the reader to assess the challenges and differences in remote sensing-based biomass estimations for these natural ecosystems.

2 Remote Sensing

One of the recent advances in biomass estimation approaches is the incorporation of inferences derived from remote sensing. Remotely sensed data have the provision of a synoptic view of the surface area of interest, thereby capturing the spatial variability in attributes of interest like tree height, crown closure, etc. The spatial coverage of large area biomass estimates that are constrained by the limited spatial extent of forest inventories may be expanded through the use of remotely sensed data. Biomass and carbon stock estimates derived from forest inventory data usually have some spatial, attributional, and temporal gaps. Remotely sensed data can be used to fill these gaps, thereby leading to estimates closer to the actual value. Remote sensing data are available at different scales, from local to global, from various sources including optical or microwave, and hence are expected to provide information which can be related directly, and in different ways, to biomass information.[23,24] Although remote sensing technology cannot effectively be used for underground biomass, it has the ability to provide important information for aboveground biomass (AGB).[3,25] A large range of studies has been conducted for biomass estimation from remote sensing data.[24,26–31] The advantages of remote sensing include the ability to obtain measurements from every location in the forest, the speed with which remotely sensed data can be collected and processed, the relatively low cost of many remote sensing data types, and the ability to collect data easily in areas which are difficult to access on the ground.[32] There are many sensors available with different characteristics of spectral, spatial, and temporal resolutions used for biomass estimation based on availability, efficiency and cost. Optical remote sensing, radar and light detection and ranging (LiDAR) sensors provide the three main sources of remotely sensed data for biomass estimation.

2.1 *Optical Remote Sensing*

Due to its coverage, repetitiveness and cost-effectiveness, optical remote sensing provides a potential alternative to tedious hand sampling as a means of estimating biomass over large areas.[33,34] Optical remote sensing data can be acquired at a variety of spatial and temporal resolutions. High-spatial resolution data from sensors such as Quickbird, WorldView, GeoEye, IKONOS, and DigitalGlobe as well as aerial photographs come in spatial resolutions ranging from submeters to <5 m in both multispectral and panchromatic images. Images at high resolution offer a fundamental shift in vegetation assessment capability where a multispectral pixel can image a single tree crown, unlike sensors with medium resolution such as Landsat or Systeme Probatoire D'Observation De La Terre (SPOT) where a single pixel can encompass many tree crowns or significant noncrown features.[35,36] Satellite data covering 10 to 100 m of ground in 1 pixel are termed as medium-spatial resolution data and Landsat time series and SPOT sensors have been the two primary sources of medium-resolution data. Coarse-resolution data (>100 m) [e.g., MODIS, national oceanic and atmospheric administration (NOAA), advanced very high resolution radiometry (AVHRR), SPOT vegetation] can be useful for biomass estimation at regional to continental scales since their high temporal frequency increases the probability of acquiring cloud-free data for generating consistent datasets over large areas. AVHRR data have been the most widely used datasets for studies of vegetation dynamics on a continental scale. However, the MODIS sensor has improved spectral and spatial resolutions compared to the widely used AVHRR and provides a suite of biophysical products that are useful in biomass estimation, including vegetation indices, leaf area index (LAI), fraction of absorbed photosynthetically active radiation (FAPAR), gross primary production, net photosynthesis, and net primary productivity (NPP).[37,38] The mid-infrared (MIR) reflectance from optical remote sensing data is closely related to biomass and thus was found to be more useful in assessing alterations in vegetation characteristics compared to reflectance in visible (VIS) and near-infrared (NIR) bands.[39] Hyperspectral remote sensing is an another important source of optical satellite data for biomass estimation. Unlike multispectral satellite sensors, hyperspectral remote sensing allows the acquisition of many, very narrow, contiguous spectral bands throughout the VIS, NIR, MIR, and thermal infrared portions of the electromagnetic spectrum.[40] This ability to collect reflectance in many narrow bands makes hyperspectral remote sensing particularly useful for extracting vegetation parameters, such as LAI, chlorophyll content, and leaf nutrient concentration.[41] Optical sensors collect data from only the aboveground vegetation and have been used mainly for aboveground biomass assessment.

A range of techniques are used with optical remote sensing data to estimate biomass.[42] A commonly used technique involves the use of vegetation indices such as ratio vegetation index (RVI), normalized difference vegetation index (NDVI) and soil adjusted vegetation index (SAVI).[43] Alternatively, remote sensing data can be used to obtain indirect estimates of absorbed photosynthetically active radiation (APAR) from the red and infrared reflectance characteristics of the vegetation.[44] The APAR gives an indication of how efficiently absorbed energy is converted into dry biomass by a vegetation type.[45] Another technique involves the use of process-based models which estimate biomass production from remote sensing data by combining canopy functioning process-based models with physical radiative transfer models.[46,47]

2.2 *Radar*

Over recent years, there has been increasing interest in synthetic aperture radar (SAR) data for aboveground biomass analyses, particularly in the areas of frequent cloud conditions where obtaining high quality optical data is difficult. The capability of radar systems to collect data in all weather and light conditions overcomes this issue. Furthermore, the SAR sensor can penetrate vegetation to different degrees and provides information on the amount and three-dimensional (3-D) distribution of structures within the vegetation.[48] Airborne SAR has been operating for many years, but since the 2000s, space-borne SAR sensors such as TerraSAR-X, Advanced Land Observing Satellite (ALOS) and Phased Array L-band SAR (PALSAR) have become available.[49] Many studies based on SAR have focused on the development of algorithms for classification and biomass estimation in closed-canopy forests.[48,50] A commonly used approach to biomass retrieval from SAR has been to establish empirical relationships between field-based estimates and single channel data.[48]

The SAR sensor can detect the horizontal (H) or the vertical (V) components of the backscattered radiation. Hence, there are four possible polarization configurations for an SAR system: horizontal transmit and horizontal receive (HH), vertical transmit and vertical receive (VV), horizontal transmit and vertical receive (HV), and vertical transmit and horizontal receive, depending on the polarization states of the transmitted and received radar signals. The SAR on the ERS satellite is VV polarized while the RADARSAT satellite is HH polarized. Radar backscatters (P and L bands) have been found to be positively correlated with major forest parameters, such as tree age, tree height, DBH, basal area, and total aboveground dry biomass.[28,51–54] A detailed review on the use of radar data for biomass estimation can be found in the literature.[55,56] Various studies have utilized radar data in biomass analyses of a range of biomes.[53,54,57,58]

There are a number of advantages to radar remote sensing compared to optical remote sensing in terms of its utility in biomass estimation in savannas. The ability of radar to penetrate cloud and haze makes it especially useful in the tropics. Furthermore, radar based sensors are active and have a controlled power outlet, which ensures consistent transmit and return rates. Thus, radar sensors can function independently of solar radiation variations, unlike optical sensors where spectral reflectance measurements are affected by variations in solar radiation.[59] On the other hand, radar use has limited applications in regional studies due to the small swath width, high costs of airborne acquisitions, lower sampling density of the large footprint waveform, and the limited extent of coverage.[48]

2.3 *LiDAR*

The two-dimensional (2-D) nature of optical remote sensing data limits its use in direct quantification of some vegetation characteristics like tree height, canopy height, volume, etc. LiDAR is a relatively new and sophisticated technology that helps to overcome this limitation due to its ability to extend the spatial analysis to a third dimension. LiDAR instruments have the ability to sample the vertical distribution of canopy and ground surfaces,[60,61] and several studies have established a strong correlation between LiDAR metrics and aboveground biomass, thus allowing estimation of biomass in forested environments.[62–64] LiDAR technology has seen considerable advancement with the advent of full waveform digitizing sensors,[65] which has allowed this tool to be increasingly used in the study of forest structures in a variety of forest environments.[66–68] It has become the most efficient technology for structural assessment since it captures landscape structural data that are suitable for volume and biomass estimation.[69] Biomass can be estimated at the individual tree level with allometric equations using LiDAR data of sufficient post spacing (e.g., >1 return/m^2).[48] A detailed review of LiDAR data application in forestry can be found in Lim et al.[70]

The 3-D LiDAR points represent latitude, longitude, and ellipsoidal height based on the WGS84 reference ellipsoid. Ellipsoidal heights are converted to elevations. There are currently two types of LiDAR in operation: (1) discrete return LiDAR (small footprint) and (2) full waveform LiDAR (large footprint).[71] Both are generally calibrated to operate in the 900- to 1064-nm wavelengths where vegetation reflectance is highest.[68] A combination of either small or large footprint LiDAR systems along with GPS and accurate time referencing allow the extraction of position in 3-D of the reflecting surface.[68] Discrete return airborne LiDAR systems are more suitable for fine-scale biomass mapping, while waveform space-borne LiDAR, e.g., The Geoscience Laser Altimeter System (GLAS) on board Ice, Cloud, and Land Elevation Satellite (ICESat) has the potential for broad-scale biomass mapping.[72,73]

Although LiDAR data have some advantages over optical data, there are a few issues that restrict its use for field applications. For example, LiDAR data analyses are not simple and require more image processing knowledge and skill and specific software. The LiDAR data acquisition process is expensive and covers smaller areas, hence study areas are still limited to specific areas and have not been applied extensively to larger areas for biomass estimation.

3 Biomass Estimation in Forests

The remote sensing methods, data types, and some examples for forest biomass estimation are shown in Table 1.

3.1 *Use of Optical Remote Sensing*

Optical remote sensing data, with a variety of spatial and temporal resolutions, have been widely used for forest biomass estimation using different types of image processing techniques.[4,7,24,29,30,84,87,117–121] For biomass estimation from optical data, the commonly used approaches are multiple regression analysis, *k*-nearest neighbor, and neural network.[24,29,30,122,123] Optical data can be used to carry out spatial stratification of vegetation from which estimates of biomass distribution can be generated. For indirect biomass estimation, remote sensing data are used to determine tree canopy parameters, such as crown diameter using multiple regression analysis or canopy reflectance models.[124,125] Different types of vegetation indices and band ratios derived from optical data are also used to extract biomass by correlating vegetation index values or band ratio values with field estimations.[87]

The ready availability of high-resolution data from a range of sensors has permitted the modeling of tree parameters or forest canopy structures. For example, Song et al.[36] estimated tree crown size from IKONOS and Quickbird images and concluded that this approach could provide estimates of average tree crown size for hardwood stands. Greenberg et al.[77] have effectively used IKONOS data (spatial resolution 4 m) in estimating crown projected area, DBH and stem density. There are numerous methods applied for the extraction of biophysical parameters using high-spatial resolution data.[126] Large scale photographs and photomensuration methods have been used to measure various forest characteristics, such as tree height, crown diameter, crown closure, and stand area.[75,127] De Jong et al.[76] used digital airborne data to estimate biomass in southern France using linear regression analysis. In another study, Thenkabail et al.[4] used IKONOS data to estimate biomass of oil palm plantations in Africa. Although high-spatial resolution and associated multispectral characteristics may become an important data source for forest biomass estimation and have attained great success, the shadows and intracrown spectral variance and the low spectral separability between tree crowns and other vegetated surfaces in the understory[128–130] create difficulty in developing

Table 1 Summary of the remote sensing methods, data types, and some examples for forest biomass estimation.

Category	Methods	Data used	Characteristics	Examples
Remote sensing-based methods	Methods based on fine spatial resolution data (<5 m) (parametric classifiers, MLC, MDM, etc.; nonparametric classifier, ISODAT, k-means)	Aerial photographs, IKONOS, Quick Bird, GeoEye, WorldView	Per-pixel level	Refs. 4, 36, and 74–77
	Methods based on medium-spatial resolution data (10–100 m) (linear, exponential and multiple regression analysis, neural network, k-nearest neighbor method, productivity model)	Landsat 4 5 7 TM/Enhanced TM + , Systeme Probatoire D'Observation De La Terre (SPOT)	Per-pixel level	Refs. 78–83
	Methods based on coarse-spatial resolution data (> 100 m) (regression models, multiple regression and artificial neural network (ANN), k-nearest neighbor, statistical models)	IRS-1C WiFS, AVHRR, MODIS, SPOT vegetation	Per-pixel level	Refs. 81 and 84–89
	Methods based on radar data (regression models, canopy height model, multiplicative models)	SIR-C, SAR-L JERS-1 SAR-L, AeS-1 SAR-P, InSAR, airborne laser, large and small footprint LiDAR	Per-pixel level	Refs. 54, 57, 72, and 90–100
	Method based on image fusion techniques (intensity hue and saturation (HIS), Brovey, PCA	Multispectral and PAN		Refs. 101–104
	Vegetation index-based method (NDVI, ratio)			Refs. 105–108
	Object based (segmentation and classification, ANNs, k-nearest neighbor, statistical models; random forest)		Object-level	Refs. 109–113
	Advanced classifier spectral mixture analysis (SVM), random forest, support vector machine (SVM)	Multispectral	Per-pixel level	Refs. 113–116

biomass estimation models. High-resolution data need large data storage and processing time and are much more expensive to cover a given area. These factors influence the application of high-spatial resolution images for biomass estimation over broad areas. The absence of shortwave-infrared images, an important parameter for biomass estimation, also limits its application in biomass assessment. The problem is greater when traditional pixel-based spectral classifiers are used for vegetation classification. However, the incorporation of contextual information and object-based methods into the classification process has overcome this problem to an extent.[109,111] Object-based methods consider both spectral and context information during the classification process by segmenting the image into meaningful objects.[110,112] The size of the image objects is determined by a scale parameter.[131] The selections of segmentation parameters are subjective and determined through a combination of trial and error steps. Statistics on spectral bands (mean, standard deviation, etc.) along with other contextual information, such as geometric features (area, length, compactness, shape, etc.), and texture features-gray-level co-occurrence matrix (GLCM) (homogeneity, contrast, entropy, dissimilarity, correlation, etc.), and gray-level difference vector (entropy, contrast, etc.) of spectral bands are used to statistically derive features for each object that best separate the vegetation classes. Numerous studies have extracted GLCM textures from remote sensing images.[111,113,132] In Rondônia State, Brazil, Lu and Batistella[113] used the GLCM texture (mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation) with different moving window sizes and Landsat thematic mapper (TM) spectral bands 2 to 5 and 7 to examine the relationships between biomass and textural images for secondary and mature forest. They found a stronger relationship between textural images and biomass for mature forest with complex stand structure than original spectral bands. However, for secondary forest with a simple stand structure, biomass was closely related to spectral bands.

Medium-spatial resolution data have also been widely used in forest biomass estimation. For example, Lefsky et al.[80] estimated stand tree structure attributes such as basal area, biomass and DBH using remote sensing data. Linear or nonlinear regression models, *k*-nearest neighbor, neural network, and vegetation canopy models are the main methods applied in this case. In a Bornean tropical rain forest, Foody et al.[82] used neural networks for biomass estimation using Landsat TM. Ghasemi et al.[133] used SPOT 5 data to estimate aboveground forest biomass from canopy reflectance model inversion in the mountainous terrain of Kananaskis, Alberta. Landsat TM data were used to estimate tree volume and biomass using the *k*-nearest neighbor estimation method.[78,79,81] The task of estimating biomass from optical data for humid tropical forests is challenging because of its complex multilayered closed canopy structure combined with high levels of biomass.[3,24,29,82,118,123,134] In such cases, spectral reflectance and vegetation indices were found not to be reliable indicators of biomass[24] and were not sensitive to biomass change.[29] However, with the inclusion of some other factors, a few studies have shown positive results in estimating tropical forest biomass. For example, Nelson et al.[123] included the age of the forest into Landsat TM image analysis to estimate tropical forest biomass, while with the use of texture information into the image analysis process, Lu[118] and Sarker and Nichol[135] improved biomass estimation results in tropical forests. Lu[118] concluded image texture features to be more important than spectral reflectance for biomass estimation for forests with more complex stand structure. However, it is critical to identify suitable image textures that are strongly correlated with biomass but are weakly correlated with each other and this requires a great deal of effort.[136] In addition, image textures vary with the landscape and images used, therefore, not all texture measures can effectively extract biomass information and guidelines on how to select an appropriate texture needs more research. Several vegetation indices have been developed, mostly from VIS and infrared bands and applied to biomass estimation and biophysical parameter studies.[105,106] Vegetation indices have been found useful in minimizing spectral variability caused by canopy geometry, soil background, sun view angles, and atmospheric conditions when measuring biophysical properties.[107,108] Although not all vegetation indices were found to be directly correlated with biomass,[24] by minimizing the impact of environmental conditions and shadow on spectral reflectance, there was improved correlation between biomass and vegetation indices, especially in complex vegetation stand structures.[105] Therefore, a combination of image textures and spectral responses can be considered useful in determining forest stand parameters and to establish more accurate biomass estimation models.[118] In addition to pixel-based spectral responses and textural images, subpixel-based variables such as green vegetation, shade, and soil can also be used as input variables for biomass estimation.[20,137] Spectral mixture analysis (SMA) has been found useful in developing these fractional images from multispectral images such as Landsat TM.[113,115] Lu and Batistella[113] used SMA to extract fractional images from a Landsat TM image to examine the relationship between biomass and the subpixel variables for secondary and mature forests in Rondônia State. They found fractional images to be more useful for biomass estimation as compared to individual spectral bands. A detailed description of the SMA approach and its applications can be found in the literature.[114–116]

Coarse-spatial resolution AVHRR NDVI data have been used to estimate biomass in Africa[86] and boreal and temperate forest woody biomass in Canada, Finland, Norway, Russia, Sweden, and the USA.[87] The advantages of a large number of spectral bands of MODIS data and their availability have improved biomass estimation accuracy at the continental or global scale. Recent studies have achieved promising results using tree-based models and metrics derived from MODIS data, in combination with radar data and ancillary information (climate, topography, and vegetation maps), to map the biomass distribution for the Amazon basin,[89] the United States,[138] and tropical Africa.[85] Baccini et al.[84] used MODIS data in combination with precipitation, temperature, and elevation for mapping biomass in national forest lands in California, USA. Overall, the application of forest biomass estimation using coarse-spatial resolution data is limited due to the occurrence of mixed pixels, saturation of spectral data at high biomass density and by the mismatch between the size of field plots and pixel size. A few studies have used coarse-resolution data along with medium-resolution data in combination with different modeling approaches to get more accurate biomass estimates for large areas. For example, Hame et al.[88] used Landsat TM and AVHRR data to estimate coniferous forest biomass. In another study, Tomppo et al.[81] used TM as an intermediate step between field data and IRS-1C wide field sensors data to estimate tree stem volume and biomass in Finland and Sweden.

Overall, optical sensor data are found suitable for extracting horizontal vegetation structures such as vegetation types and canopy cover; however, the 2-D data have limitations in estimating vertical vegetation structures such as canopy height, which is one of the critical parameters for biomass estimation. Recently, optical data such as ALOS, panchromatic remote-sensing instrument for stereo mapping (PRISM), IKONOS stereo satellite images, and SPOT provide a stereo viewing capability that can be used to develop vegetation canopy height, thus can improve biomass estimation performance.[139,140] For example, St-Onge et al.[139] assessed the accuracy of the forest height and biomass estimates derived from an IKONOS stereo pair and an LiDAR digital terrain model. Reinartz et al.[141] used SPOT 5 HRS for forest height estimations in Bavaria and Spain, while Wallerman et al.[142] investigated 3-D information derived from SPOT 5 stereo imagery to map forest variables such as tree height, stem diameter and volume. These studies show that high-resolution stereo data can be used as a valuable alternative to derive vegetation height information; however, more studies are needed to support this.

3.2 *Use of Radar*

Studies that utilized radar data in forest biomass estimations found SAR L-band data to be more useful[53] than SAR C-band data.[90] Beaudoin et al.[143] found that VV and HV radar backscatter at high frequencies (C-bands and X-bands) were linked to crown biomass while radar backscatter HH at lower frequencies (P-bands and L-bands) were related to both trunk and crown biomass. Harrell et al.[144] used SIR C- and L-band multipolarization radar data for pine forest biomass estimation in the southeastern USA and found L-band HH data to be critical in biomass estimation. They noted that the inclusion of C-band HV or HH significantly improved biomass estimation performance. For biomass estimation of regenerating forests, Kuplich et al.[91] found JERS-1/SAR data to be useful when forests are regenerating after block logging and not after selective logging. For mountainous area forest biomass estimation, multipolarization L-band SAR data were found to be useful.[53] Santos et al.[92] found that JERS-1/SAR double bounce scattering and forest structural-physiognomic characteristics are the two important factors for biomass estimation of forest and savanna. For biomass estimation, most of the previous studies used the radar system from JERS-1, ERS-1/2 of single polarization, single incident angle, and low resolution SAR sensor. However, with the establishment of PALSAR and RADARSAT-2 (C-band), data are now available in different polarizations, different resolutions, and varying incident angles, which offer more opportunities to the scientific community to re-examine the potential of SAR data in forest biomass estimation. PALSAR data results have shown its ability to map forest in the Amazon and Siberia; however, the retrieval of forest biomass is still typically limited to values less than 50 $\mathrm{t\,ha^{-1}}$, which excludes most temperate and tropical forests.[145] Sarker et al.[57] investigated the capability of RADARSAT-2 fine-beam dual-polarization (C-HV and C-HH) data for forest biomass estimation in complex subtropical forest and found encouraging results. Radar data saturation problem is greater in complex forest stand structure when backscattering values are used for biomass estimation.[146,147] Interferometry SAR (InSAR) has been found useful in reducing this problem by increasing the saturation range to a certain degree by coherently collecting data over a short time increment with two identical instruments.[93,94,133] This improves the height-based biomass and volume estimation when the L-band saturation point increases to 200 $\mathrm{t\,ha^{-1}}$.[73] Balzter[93] reviewed InSAR for forest mapping and monitoring covering tree volume and biomass, forest types and land cover, fire scars, forest thermal state, and forest canopy height. The high correlation between vegetation canopy height and biomass of InSAR makes it a promising tool for broad-scale biomass estimation, especially for tropical and subtropical regions where frequent cloud cover is a problem.[94,95] However, other weather conditions, such as wind speed, moisture, and temperature, affect the InSAR estimation accuracy.[148] Recently, the polarimetric SAR interferometry (Pol-InSAR), a combined polarization and interferometry, has been found useful in estimating forest height using coherence information[149] and then correlating it to biomass.[150]

3.3 *Use of LiDAR*

The structural forest measurements from LiDAR data permit the accurate estimation of height, crown size, basal area, stem volume, LAI, NPP, and aboveground biomass, even in high biomass forests, a difficult task with passive sensors.[66] Biomass mapping from airborne discrete return LiDAR is based on two approaches: (1) area-based and (2) individual tree-based methods.[72] Area-based methods develop statistical models to relate biomass with metrics derived from a LiDAR point cloud at the plot or stand level and apply the models over the whole study area.[151–97] The development of statistical models requires field data for calibration and validation. The most widely used area-based LiDAR metrics for biomass prediction are various height metrics[70,152,153] calculated based on first, last, or all returns. Height metrics can also be calculated from grids of the canopy height model.[96,139,152] Individual tree-based methods identify individual tree crowns and extract individual tree information from LiDAR point cloud, such as tree height and crown size, which can be related to biomass and other canopy structure variables through allometric equations. [154–156] In this case, the amount of fieldwork required is much smaller than that for area-based methods because field data are needed only for a sample tree and not for sample plots or stands. Discrete return systems have been used to estimate biomass at the individual tree level up to the stand level.[154,155,157,158] The DEMs generated from airborne LiDAR data are very accurate and widely used in forest mapping and tree parameter estimations. It captures elevation information from the forest canopy as well as the ground beneath and can be used to assess the complex 3-D patterns of canopy and forest stand structure such as tree density, stand height, basal area, LAI, and forest biomass and volume.[68,159] In densely vegetated areas when passive sensors saturate at high biomass levels (higher than 100 mg ha^{-1}),[160] LiDAR has been found to accurately estimate LAI and biomass in such high biomass ecosystems.[68] In British Colombia, Canada, Loos et al.[161] identified understory canopies between the dominant canopies of Douglas-Fir and Western Hemlock tree species by creating bare earth DEM and DSMs (digital surface models). The estimation of biomass is generally based on regression equations relating vegetation biomass to LiDAR derived variables. Studies are being conducted using LiDAR to determine the most appropriate laser-based predictors in regression models for estimation of forest structural variables. For example, García et al.[162] have explored several biomass estimation models based on LiDAR height or intensity, separately, or height-intensity combined. They found height-related variables provided accurate estimation of biomass; however, normalized intensity-related variables were found to be more useful in explaining variance and also estimated biomass more accurately. The combined use of height and intensity data has been shown to be a robust method to estimate biomass. For broad-scale applications, space-borne LiDAR (ICESat GLAS) was found useful for biomass estimation.[98–100] The waveform extent of GLAS is the most important metric for biomass estimation[100] as it is directly related to vegetation height in flat terrain; however, for sloped areas, waveform exacerbates estimation and needs terrain steepness index into a regression model.[100]

In summary, remote sensing data (optical, SAR, LiDAR) have been found to be a major source of data for forest biomass estimation and also in the selection of suitable variables important for developing biomass estimation models. However, the performance of remote sensing data and methods in biomass estimation have been found to be highly dependent on image data type, forest cover type and state, geographical and environmental conditions and methods used. Optical data are found suitable for extracting horizontal vegetation structures such as vegetation types and canopy cover and also in extracting variables for biomass estimation models. They have been used for biomass estimation of almost all forest types, either alone or in combination with other remote sensing data with varying degrees of success. However, optical data have an issue of clear weather condition at the time of data acquisition and also of saturation problems in forest sites with high biomass density. Spectral-based variables have been found to be influenced by external factors such as soil moisture, vegetation phenology and growth vigor, and also the 2-D nature of optical data limits its use in estimation of vertical vegetation structures such as canopy height, a critical parameter for biomass estimation. Recently, data from ALOS/PRISM and other stereo images have provided an opportunity to develop vegetation canopy height and can improve biomass estimation performance. Radar data can overcome many of the optical data problems for forest biomass estimation because of its ability to penetrate forest canopy to a certain depth, its sensitivity to water content in vegetation and its weather independency. The regression of radar backscattering (amplitudes) and interferometry (amplitudes and phases) are commonly used methods in biomass estimation. Radar data have been used extensively in forest cover and type mapping, estimation of forest stand parameters and in estimating biomass in tropical, temperate and boreal forests. However, radar data suffer from saturation problems in complex mature forest stands and also have difficulty in distinguishing vegetation types. L-band SAR images have been found suitable in discriminating forest biomass up to a certain threshold of regenerating forests in tropical regions. PALSAR data have shown its ability to estimate forest biomass in the Amazon and Siberia up to 50 $t\,ha^{-1}$, which excludes most temperate and tropical forests. The stereo viewing capability of InSAR data has been found to improve biomass estimation in more complex forest stands and has been found useful in reducing saturation problems by increasing the saturation range to a certain degree. The high correlation between vegetation canopy height and biomass of InSAR makes it a promising tool for broad-scale biomass estimation for tropical and subtropical regions of frequent cloud cover. However, InSAR biomass estimation accuracy has been found to be sensitive to weather conditions. Improved systems, such as Pol-InSAR, have been found useful in estimating forest height and biomass estimation. LiDAR sensor can directly measure 3-D components of vegetation canopy structure and is widely used in estimation of forest biophysical parameters. Discrete return small footprint laser data are used for biomass estimation for different forest environments: tropical forest biomass, temperate mixed deciduous forest biomass; and also in measurements of biophysical parameters such as tree height and stand volume, tree and crown diameter, and canopy structure. For regional to global scale applications, spaceborne LiDAR (ICESat GLAS) has been found useful for biomass estimation.

4 Biomass Estimation in Grasslands and Rangelands

Grassland and rangeland ecosystems cover large areas of the earth's surface and provide many ecosystem services including carbon storage, biodiversity preservation and the production of livestock forage.[163] Being dominant over approximately 52.5 million square kilometers (near 40%) of the Earth's land surface,[164,165] grasslands and rangelands are important sources for developing renewable energy. They can provide an alternative source for energy supply which reduces the dependence on fossil fuels and minimizes greenhouse gas and other environmental impacts.[166] In addition to biofuel production, grassland ecosystems play an important role in providing food, goods, and services for humans, and are central to livestock grazing.[167,168]

4.1 *Use of Optical Remote Sensing*

Optical remote sensing has been extensively used for estimating grassland and rangeland biomass. Coarse-, medium-, and high-spatial resolution images have been used and examined in order to better map the distribution of grassland and rangeland biomass. For example, Li et al.[169] used multitemporal MODIS data to estimate the grassland aboveground biomass in the West Songnen Plain, China. Their results indicated that multitemporal remotely sensed data along with statistical models and artificial neural network (ANN) techniques have advantages for estimating grassland aboveground biomass. Mundava et al.[170] used Landsat ETM+ to test the relationship between AGB in rangelands and remotely sensed indices by measuring dry and green biomass fractions and found that single vegetation indices were moderately more accurate for green biomass than dry biomass. For high-spatial resolution images, Dusseux et al.[171] estimated grassland biomass in agricultural areas by applying NDVI and two biophysical variables including LAI and fraction of vegetation cover on five SPOT images. Zandler et al.[172] found that both a high-spatial resolution sensor (RapidEye) with its additional red edge band and a coarse-spatial resolution sensor (Landsat-8) showed very similar performances for modeling the total dwarf shrub biomass in the desert landscape. The red edge reflectance curve performs better than traditional vegetation indices for estimating the distribution of grassland over a desert environment.[173,174]

Hyperspectral remote sensing data were also used to estimate grassland and rangeland biomass. Among others, Rahman and Gamon[175] examined the utility of hyperspectral remote sensing to detect fresh and dry biomass, water content and plant area index of burned and unburned grassland in Southern California. Xiaoping et al.[176] concluded that grassland and rangeland biomass could be estimated at the canopy level using hyperspectral reflectance. Clevers et al.[177] found that one band in the NIR region from 859 to 1006 nm and one band in the red edge region from 668 to 776 nm that were used in the weighted difference vegetation index had the best predictive power of grassland biomass variation.

4.2 *Use of Radar and LiDAR*

Despite the popularity of radar and LiDAR data in forest biomass analyses, very few studies have utilized such data in the estimation of grassland biomass. For instance, Dusseux et al.[178] compared the performance of variables extracted from four optical and five SAR satellite images to monitor grassland biomass. They concluded that the classification accuracy of SAR variables was higher than those using optical data. Buckley and Smith[58] used radar, LiDAR, and hyperspectral data to monitor grassland biomass and they argued that radar and LiDAR data were not affected by weather conditions as optical remote sensing data is.

Vegetation indices, including SAVI,[179] the modified soil adjusted vegetation index (MSAVI),[180] NDVI,[181,182] and normalized difference water index,[183] have been widely used in grassland and rangeland biomass estimation. Image classification, such as support vector machine classifier,[177,184] object-based classification,[185] and ANN,[182] were other techniques frequently used for deriving grassland and rangeland biomass. In addition, multiple regression analysis models were the most commonly used statistical approaches.[186] However, the performance of these techniques varied and depended on the structure of the study area and the nature of the remotely sensed data used to estimate grassland and rangeland biomass.

5 Biomass Estimation in Tropical Savanna

Savanna ecosystems are generally comprised of herbaceous plants dominated by grasses, with variable tree cover.[187,188] These ecosystems cover approximately 18% of the Earth's surface and account for approximately 30% of the primary production of all terrestrial vegetation, thus forming an integral part of global vegetation.[189,190] The largest areas of savanna can be found in Africa where it occupies approximately 50% of the territory.[191] Considerable areas of savanna can also be found in South and Central America, Australia, India, Southeast Asia, and the Pacific Islands.[192–197] Furthermore, savanna ecosystems are characterized by a pattern of strong seasonality in available soil moisture, determined by a wet-dry climate.[195,198] This seasonality in water availability impacts plant productivity and consequently biomass production in savanna ecosystems.[195] Tropical savanna ecosystems can be highly productive with a global average NPP ranging from 720 $\mathrm{g\,C\,m^{-2}}$ year-1143 to 782 $\mathrm{g\,C\,m^{-2}}$ year-1199. The arid and semiarid savannas of Africa, Australia, and South America show lower NPP compared to the margins of the Amazon and Congo River basin.[199] Fire is also a dominant feature and a major determinant of the ecology and distribution of savannas worldwide.[190,200,201] Thus, fires have an impact on the proportions of dead and live biomass in savannas.[202]

The rate of biomass production is an important attribute of most ecosystems. In the savanna ecosystem, as in all ecosystems, the rate of biomass production determines the amount of energy available for higher trophic levels.[203] Thus, biomass estimation will provide crucial information on the health of the ecosystem and the biodiversity it supports. Additionally, there is a growing recognition of the value of natural carbon stores in savanna biomass and the significance of savannas in the global carbon cycle.[190] These ecosystems also face increasing pressure from human interventions in the form of agricultural expansion,[187,204] logging and burning.[187,205] Given the important role of savanna ecosystems in the global carbon cycle and the threats they face, it is vital to undertake a detailed census of biomass in these ecosystems. Techniques that will reliably measure, map and monitor biomass in savanna ecosystems are required that will support conservation and management actions, as well as determine optimum use for renewable energy. Field measurements to estimate biomass are labor intensive and time-consuming. Remote sensing and LiDAR sensors provide many opportunities in this respect.[206]

Remote sensing and LiDAR systems have quite commonly been used in biomass assessment of closed forests; however, their use in savannas has become more popular only in recent times. The main reasons for this are that the distribution of vegetation biomass in savannas is uneven in 3-D space with biomass allocated to above and below ground components.[48] Furthermore, the structure of savanna vegetation is variable with the occurrence of an herbaceous layer with variable tree cover and open spaces.[188] These two factors make the retrieval of savanna vegetation characteristics from remote sensing data difficult.

5.1 *Use of Optical Remote Sensing*

Vegetation indices have been used extensively by researchers in the context of savanna ecosystems.[207–211] For example, Sannier et al.[212] found high correlations of biomass with NDVI from NOAA–AVHRR images for both herbaceous and woody vegetation in the savanna region of Etosha National Park in Namibia. Other studies have also shown the sensitivity of NDVI to the herbaceous biomass of savannas in the Sahel zone of Senegal using NOAA–AVHRR imagery.[16,213] On the other hand, Mutanga and Skidmore[106] found that the NDVI performed poorly in estimating pasture biomass of *Cenchrus ciliaris* grass in the low-lying savannas of Kruger National Park in South Africa. They suggest that some indices, such as the NDVI, had limited value in biomass estimation since they saturate in dense vegetation, a finding that agrees with Gill et al.,[214] who found that the NDVI had limited application in monitoring changes in vegetation in Australia due to saturation. Indices such as simple ratio or RVI and the red edge position may perform better, particularly when estimating pasture biomass with high canopy density.[106] Verbesselt et al.[215] used RVI from SPOT vegetation time series to monitor the vegetation biomass in the savanna ecosystem of Kruger National Park in South Africa. On the other hand, van Leeuwen et al.[216] argued that soil background influences altered the responses of most vegetation indices and thus utilized SAVI in their estimation of herbaceous biomass using reflectance data in a shrub savanna landscape in Niger.

Monteith's efficiency model using indirect estimates of APAR obtained from remotely sensed data has been applied in the African Sahel to assess the productivity of savanna ecosystems.[217,218] The findings support the idea that savannas play an important role in global carbon cycle, particularly given the large areas that they cover. Other global savanna biomass assessments have been made possible through NASA's Terra satellite platform with MODIS on board. Fensholt et al.[37] have utilized LAI, FAPAR, and NPP produced by MODIS in estimating biomass production in the savannas of the semiarid Sahel zone in Senegal. An assessment of the MODIS LAI product for Australian ecosystems revealed that the savanna and shrub-land group LAIs show strong seasonal patterns, mainly associated with summer rainfall seasons.[219]

Process-based models are becoming increasingly popular in studies involving productivity assessments of terrestrial ecosystems.[220–225] These studies combined satellite "greenness" data from the AVHRR sensor into the NASA–Carnegie Ames Stanford Approach (CASA) model to estimate spatial variability in global biomass accumulation in terrestrial ecosystems. Potter et al.[220] applied a similar methodology but used MODIS EVI data, which represent the optimized vegetation index from the MODIS satellite, to estimate aboveground biomass (AGB) in savanna ecosystems worldwide and found it to be second only to tropical evergreen forests. However, the MODIS data also showed that the productivity of savanna ecosystems worldwide is highly dependent on seasonal climate anomalies such as El Niño Southern Oscillation.[225] For example, research conducted on the Brazilian Amazon Cerrado (savanna) established that the productivity of the Cerrado was highly impacted by variability in precipitation rates caused by the 2002–2003 El Niño phase.[220,226] The general pattern observed was an increase in seasonal FPAR cover in savannas during increased precipitation and decrease in FPAR cover during reduced precipitation (FPAR is an indicator of biomass production). This pattern suggests that the productivity of savanna ecosystems is very dependent on future rainfall patterns, particularly in parts of the world that are likely to be affected by climate change.[199]

5.2 *Use of Radar and LiDAR*

McGlinchy et al.[65] have used LiDAR for biomass estimation in savanna ecosystems with some success in a South African savanna landscape. Others have utilized new approaches involving the fusion of high-fidelity VIS/NIR imaging spectrometer data with scanning, waveform light detection and ranging (wLiDAR) data to assess biomass in African savannas.[206,227,228] The findings established the potential of fused hyperspectral and wLiDAR data for herbaceous biomass modeling in savannas.

Collins et al.[59] examined the relationship between the backscatter intensity of polarimetric SAR data and the aboveground biomass of a north Australian savanna to estimate above and below ground biomass and carbon storage of this ecosystem. They found no significant difference between their predicted and observed aboveground biomass, thus demonstrating the potential of SAR for predicting and mapping aboveground biomass in the tropical savannahs of northern Australia. However, the open canopy of savannas and the spatial resolution of the sensor lead to complications for the use of SAR data in savannas.[48] For example, Viergever et al.[229] evaluated SAR data for aboveground biomass estimation in tropical savanna woodland in Belize, Central America. Their findings showed a relatively low correlation between SAR backscatter and aboveground biomass, although retrieved canopy heights gave a better representation of the aboveground biomass. Nevertheless, it could not be used to estimate biomass directly due to the heterogeneity of the canopy.

Savannas are extremely productive systems and they have a lot of potential for renewable energy through biomass, making it very important to develop accurate and precise methods for estimating biomass. These ecosystems also face many threats, both human and climate change induced. Remote sensing can provide cost-effective and timely biomass estimates over large areas as opposed to direct field measurements of biomass which are labor intensive, costly and sometimes destructive.

6 Image Processing for Biomass Estimation

6.1 *Spatial Data Processing*

Although a range of remote sensing data (optical, radar, LiDAR) at different spectral, spatial, and temporal resolutions have been used for biomass estimation with varying degrees of success, it has been found that improvement in biomass estimation depends not only on the data type but also on efficient image processing techniques.[230] There are a number of environmental and topographic factors that can affect the accuracy of biomass estimation from remote sensing data. A thorough understanding of previous efforts in biomass estimation can be used in designing an optimal image analysis procedure suitable for the specific study area. Radiometric and atmospheric corrections are important in improving image quality, and a range of methods have been developed for these corrections under different conditions.[231] Topographic factors (slope, aspect) that affect vegetation reflectance and biomass are also important for mountainous regions. More details on these corrections can be found in Hale and Rock.[232] The problem associated with remote sensing data for biomass estimation is that the images become saturated at fairly low biomass levels. Use of narrow-wavelength images can reduce this data saturation problem.[106] The large number of spectral bands in the hyperspectral image may improve the biomass estimation performance. However, because of data volume and processing time, there is often a trade-off between spatial, spectral, and radiometric resolutions.

Image classification is the simplest way of extracting information from remote sensing data, and a range of classification algorithms are available for different data types and conditions. The conventional pixel-based classification method, relying only on spectral information, works well with medium- to coarse-resolution images but is often found insufficient when applied to very high-resolution imagery[233] and LiDAR. Object-based classification methods based on both spectral and contextual information have been shown to improve performances for many applications, including biomass estimation.[234] However, the implementation of contextual information in classification is a complex process.[136] Use of advanced classifiers, such as SMA, can also improve classification results.[113]

6.2 *Image Fusion*

Most previous studies involving biomass estimation from remote sensing data have used a single sensor or single date image, which may not be sufficient for complex applications such as biomass estimation in certain areas.[31,101] Since remote sensing data are available from a range of sensors, each with its own characteristics and time series, it would be more useful if they were combined or fused to produce a better understanding of the observed site.[102] For example, the fusion of optical and radar data may reduce mixed pixels and data saturation problems and has the potential to improve biomass estimation. Multisensor or multiresolution data fusion takes advantage of the strengths of distinct image data for improvement of visual interpretation and quantitative analysis[3] and numerous methods have been developed to integrate spectral and spatial information from different sensors.[103,104,235,236] Studies in the past have shown that the fusion of optical (multi and PAN) and also SAR data resulted in an improved performance for biomass estimation.[237–241] However, more research is needed to explore the improvement of biomass estimation through multisensor data fusion. Several studies have also tried to combine high-resolution multispectral imagery and LiDAR data to produce more effective forest classification.[242–245] Tonolli et al.[246] studied the prediction of forest stem volume using LiDAR and IRS 1C, LISS III data. Popescu et al.[125] explored the feasibility of small footprint LiDAR and multispectral imagery to estimate volume and biomass in deciduous and pine stands in Virginia, USA. The results showed that, though LiDAR accurately estimated the biophysical parameters of forest stand at the individual tree level alone, it was more effective when used in conjunction with optical data. Vaglio-Laurin et al.[247] estimated aboveground biomass in an African tropical forest with LiDAR and hyperspectral data. Their findings showed that the integration of hyperspectral bands with LiDAR improved the model based on LiDAR or hyperspectral bands alone.

7 Remote Sensing Techniques and Accuracies Among Forest, Grassland/Rangeland, and Tropical Savanna Ecosystems

The environmental structure for forests, grasslands/rangelands, and tropical savanna biomes is different based on the nature, distribution, characteristic, density, and energy produced from each ecosystem. These elements interact with incoming radiation to impact remote sensing data and affect the information provided. In the past, a wide range of remote sensing techniques has been used to extract information related to biomass estimation from forests, grasslands/rangelands and savanna ecosystems. Most of the techniques used were vegetation indices, image transform algorithms [e.g., principal component analysis (PCA), minimum noise fraction transform (MNF), and tasselled cap transform (TCT)], texture images, radar, and LiDAR. However, these techniques have shown different accuracies in various ecosystems.

Based on vegetation extraction using remote sensing data, the most frequently used techniques for forest, grassland/rangeland and savanna ecosystems are vegetation indices. The common vegetation indices have included NDVI, EVI, SAVI, and NDBI and have been used to estimate biophysical variables including LAI, FAPAR and biomass. In biomass estimation, however, vegetation indices can be a more suitable technique for grassland, savanna and forest sites with a simple stand structure rather than those of a complex stand structure since the relationships of NIR wavelength with biomass are weak.[20,115] Lu et al.[115] found that the relationships of shortwave-infrared wavelength with biomass are stronger than the NIR wavelength in a complex stand structure. Roy and Ravan[122] emphasized the strength of shortwave infrared in the relationships between spectral response and biomass, but these relationships have a seasonal dependency in varying phonological conditions. This is because the shortwave-infrared bands are less affected by atmospheric changes. For grasslands/rangelands and savanna biomass estimation, the performance of vegetation indices has shown differing accuracies. For example, Ullah et al.[248] concluded that band depth analysis consistently showed a higher accuracy than vegetation indices using MERIS data in grassland ecosystems, while Paruelo et al.[249] found a positive relationship between NDVI and aboveground net primary production (ANPP) with mean annual precipitation between 280 and 1150 mm, and mean annual temperature between 4 deg and 20 deg using AVHRR/NOAA. However, Mutanga and Skidmore[106] emphasized that NDVI provides a poor performance in estimating pasture biomass. Thus, the accuracy obtained by applying vegetation indices in grasslands/rangelands and savanna ecosystems depends on a number of variables including type of data used, study area characteristics and environmental and atmospheric conditions. Additionally, the problem of saturation under high vegetation density limits the performance of vegetation indices.

Classification and linear or nonlinear regression have also shown different results and accuracies among different ecosystems. While, for example, *k*-nearest neighbor analysis provided a consistent accuracy when applied for forest biomass estimation,[250,251] it may not be a reliable technique for grassland/rangeland and savanna biomass estimation. The *k*-nearest neighbor analysis failed in some cases[250] to provide a higher accuracy when applied to large area vegetation detection. Applying hyperspectral remote sensing may overcome some of the problems, however, hyperspectral data are mainly airborne and are captured over small areas.[20] ANN has been applied to estimate biomass from both forest and grassland ecosystems. For example, Xie et al.[182] compared ANN and multiple linear regression to estimate grassland aboveground dry biomass in Mongolia and Wang and Xing[252] applied ANN to estimate natural forest biomass in Jilin Province, China. Both studies provided improved accuracies using ANN for both grassland and forest biomass estimation. Other techniques, such as image transformation (PCA, MNF, and TCT), texture analysis, and SMA, have shown differences between the obtained results of biomass estimations of forest, grassland/rangeland and savanna ecosystems. However, most previous studies have applied these techniques only for forest biomass estimation rather than for other environments.

Although LiDAR has improved the accuracy of biomass estimation in forest biomes,[67–255] the availability of LiDAR data, particularly for large areas, has limited the usefulness of this technology. Similarly, while radar data have been widely applied in forest biomass estimation (as discussed in Sec 3.2), very few studies have used radar data for biomass estimation in grasslands/rangelands and savanna ecosystems.

8 Conclusions

To efficiently and effectively use biomass as a renewable energy source, it is important to have a detailed knowledge of its distribution, abundance, and quality. Remote sensing offers the technology to enable rapid assessment of biomass over large areas relatively quickly and at a low cost. It is a technology that can be used to ensure that biomass as a renewable energy source is used in a sustainable manner. Remote sensing techniques have many potential benefits in biomass estimation over traditional field measurement methods at different scales ranging from local to regional, including cost, labor, and time. However, the selection of suitable remote sensing data based on information on the scale of the study area, the data analysis procedure and costs is an important factor to be considered for the most appropriate aboveground biomass estimation procedure. High-spatial resolution data from both airborne and satellite platforms can provide accurate biomass estimates at local scales; however, for regional scales, a large volume of data is required, which is not only expensive but also difficult to process; this limits its application for larger areas. Landsat TM (medium-spatial resolution) data have been found more effective for biomass estimation at a regional scale; however, mixed pixels and data saturation problems have been reported with these data in biomass estimation for complex environments. At the national and global scales, coarse-spatial resolution data, such as AVHRR or MODIS, have been found useful in biomass estimation; however, the data have not been used much because of the difficulty in linking coarse-spatial resolution data and field measurements. Most of the previous studies based on radar systems in biomass estimation used single polarization, single incident angle, and low resolution SAR sensor, and hence have attained limited success. However, data from PALSAR and RADARSAT-2 with different polarizations, resolutions, and incident angles can offer greater opportunity to re-examine the potential of SAR data in biomass estimation. With the advent of LiDAR systems, the analysis can be extended to the third dimension in quantifying some vegetation characteristics directly, such as tree height, canopy height, and volume and can assist in improved biomass estimation. Overall remote sensing data, ranging from optical to microwave and also to LiDAR, have shown great potential in biomass estimation at all scales.

Biomass estimation from remote sensing data is a complex analysis process which involves many factors such as mixed pixels, data saturation, and complex biophysical environments. The selection of suitable algorithms for information extraction is also difficult and needs higher analytical skills. The most commonly used methods for biomass estimation are linear or nonlinear regression models, neural network, and k-nearest neighbor, and also biomass is estimated indirectly from remotely sensed canopy parameters. Use of contextual information along with the spectral information has proven useful in improving biomass estimation. Advanced classifiers, such as SMA, can also improve classification results. The fusion of multisensor and multiresolution data may reduce mixed pixels and data saturation problems and has the potential to improve biomass estimation.

Anthropogenic actions have diminished the size of this pool of renewable energy over the years. Additionally, issues of biodiversity conservation and soil and water protection will restrict the amount of biomass that can ultimately be retrieved from forests and other land cover types.[256] Also, in order to be truly renewable, the removal of forest biomass must be undertaken sustainably so that impacts on local ecosystems and their biodiversity are limited.[14] Remote sensing can play an effective role in determining the areas from which plant biomass can be sustainably harvested and used in energy generation.

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