MODELING LEAF CHLOROPHYLL CONTENT IN HETEROGENEOUS FOREST USING HIGH RESOLUTION MULTISPECTRAL IMAGE: A CASE STUDY OF BAVARIA FOREST NATIONAL PARK

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February, 2016

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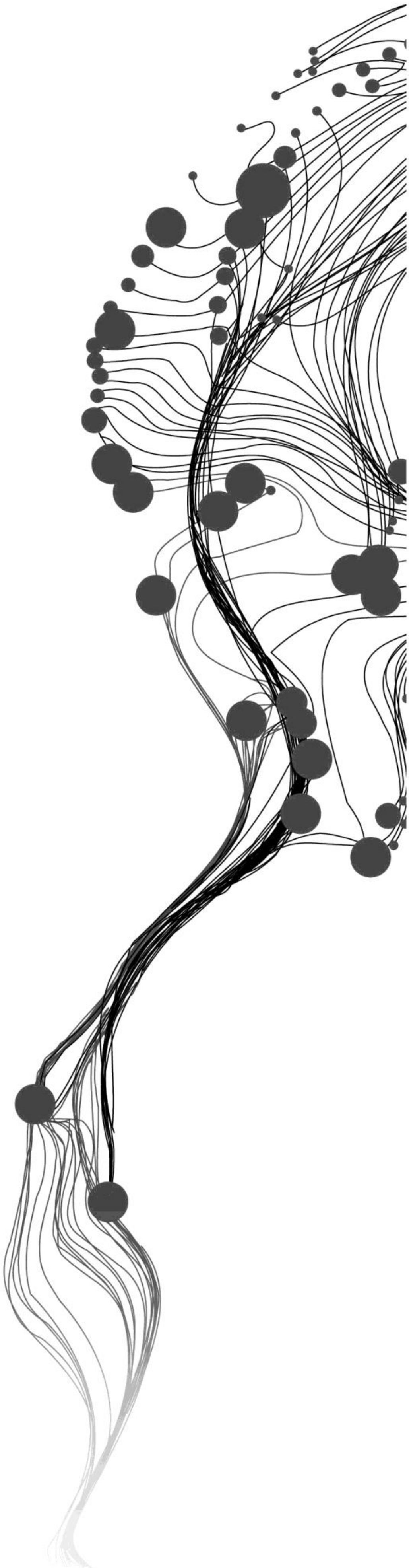

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Dedicated To: My Late Brother ‘Wogayew Cherenet’
I wish I would have been there!!

ABSTRACT

Chlorophyll is one of the main foliar biochemical components of plant playing a key role in controlling photosynthesis, plant health and physiological activities. Remote sensing methods of chlorophyll retrieval are non-destructive and can be applied for large-scale estimation of chlorophyll. In this study we evaluated the potential of high resolution multispectral satellite imagery and INFORM canopy radiative transfer model for retrieval of leaf chlorophyll content using Look Up Table (LUT) inversion. Beside this, the potential of red edge band in RapidEye image for leaf chlorophyll estimation was also evaluated.

Leaf samples were collected from 40 plots in Bavaria Forest National Park (BFNP), Germany, in July 2015 concurrent with the time of the RapidEye images. Leaf chlorophyll were obtained from the leaf samples using wet chemical analysis. Sensitivity analyses were performed to evaluate the importance of each input parameters included in the INORM model. Prior information from the field and sensitivity analysis were used to parameterize the INFORM model and to build different LUTs using systematic and random selections of input variables. Next, Top Of Atmosphere reflectance data were calculated from the satellite images and used as inputs during the inversion of LUTs. The model performance was checked based on the accuracy assessment criteria of RMSE & R^2.

The result of sensitivity analysis revealed that the forest parameters affecting reflectances in the studied wavelength region are Stand density, Leaf area index, canopy diameter, height, average leaf angle, and chlorophyll content. The relationship between the measured and estimated leaf chlorophyll using the randomly generated LUT had RMSE=8.07ug/cm^2 and R^2=34.53%. While, this relationship was weaker using the LUT generated systematically (RMSE=13.18ug/cm^2, R^2=25.48%). An increment of 5.1ug/cm^2 error (RMSE) for leaf chlorophyll retrieval was found when the red edge band was excluded from the modelling. This result indicated the importance of the red edge band for estimating leaf chlorophyll. Furthermore, after removing the blue band which was apparently affected by the atmospheric errors an improvement was observed in the model accuracy (RMSE=6.66ug/cm^2, R^2=36.74%). This emphasized the importance of band selection during inversion. The simulated spectra from the randomly generated LUT showed a closer match to the measured reflectance compared to simulated spectra from systematically generated LUT which apparently enforced the ill posed problem. Overall, in this study INFORM had shown moderate suitability potential for estimating leaf chlorophyll content under heterogeneous forest condition using RapidEye satellite data. Further studies are required to assess the potential of INFORM model and multispectral satellite data for retrieval of leaf chlorophyll using different atmospherically corrected images.

Key word*: INFORM Leaf chlorophyll, Heterogeneous Forest, RapidEye, Red edge, Look up Table*

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To God the almighty will be all the glory!!

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ALA	Average Leaf Angle
ANN	Artificial Neural Network
CW	Water Content
CM	Dry matter Content
Cab	Chlorophyll *a* and *b*
CD	Crown Diameter
CHRIS	Compact High Resolution Imaging Spectrometer
EM	Electromagnetic spectrum
FAO	Food Agricultural Organization
H	Height
INFORM	Invertible Forest Reflectance Model
IKONOS	High resolution Satellite Operated by Digital Globe
LAI	Leaf Area Index
LUT	Look Up Table
MAE	Mean Absolute Error
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multispectral Satellite Image
NIR	Near Infrared
RMSE	Root Mean Square Error
R2	Coefficient of Determination
RTM	Radioactive Transfer Model
SPOT	Satellite Pour 1'Observation de la Terre or Earth Observing Satellite
SD	Stand Density
TOA	Top of Atmosphere
TM	Thematic Mapper
UTM	Universal Transfer Mercator
WGS	World Geodetic System

1. INTRODUCTION

1.1. Background and motivation

The biochemical parameters of the plants are among the most influential components controlling the overall physiological and photosynthetic activities (Cornelissen et al., 2003). Leaf biochemical parameters such as chlorophyll, carotenoids, nitrogen and water content are among the main biochemical parameters of vegetation(Curran, 1989). The fact that, most plant biochemical parameters share similar function within the ecosystem has made these parameters to be useful for studying various ecological characteristics (Homolová et al., 2013). Ecologist have used these parameters to study the interaction between the ecosystem and biological inhabitants in a given ecosystem for example, for assessing changes in plant health associated with any environmental stress and disease (Garnier et al., 2007), assessing ecosystem productivity (Lavorel et al., 2011; Orwin et al., 2010), climate studies (Pereira et al., 2013), and assessing plant gross primary productivity (Gitelson et al., 2006).

Chlorophyll pigments are depicted as the most influential leaf biochemical parameters influencing the overall photosynthetic activities of the plant(Clevers & Kooistra, 2012; Cracknell et al., 2009; Gitelson et al., 2006). Chlorophyll is also recognised as one of the key essential biodiversity variables by the Group on Earth Observations Biodiversity Observations Network(GEO-BON) that can be monitored by remote sensing(Skidmore et al., 2015).

Chlorophyll pigments in plants exhibit in the form of chlorophyll *a* and *b* which have distinct spectral absorption properties(Lichtenthaler & Buschmann, 2001). Both forms of chlorophyll pigments are useful for facilitating energy conversion in plants system. The total leaf chlorophyll content expressed in mass per unit area of leaf is primarily accountable for any photosynthesis activity taking place in the leaf and plays a significant role in energy capturing and conversion process(Gitelson et al., 2006; Sims & Gamon, 2002).Chlorophyll pigment in plants also plays a key role for detecting the status of plant growth, primary productivity, nutritional and environmental stresses (Pallardy, 2008; Pavlovic et al., 2014; Zarco-Tejadaet al., 2000). Previous studies have demonstrated the role of chlorophyll pigments for tree species identification and habitat quality assessment(Castro-Esau et al., 2006; Delegido et al., 2014), implementing precision farming like spotting the declining process of forest resources (Navarro-Cerrilloa et al., 2014) and studying crop net primary productivity(Haboudane et al., 2002). Chlorophyll has a strong relationship with some of the plant biochemical properties such as nitrogen, therefore, quantifying one of these parameters can indirectly tell us the concentration level of the other one in the leaf (Daughtry et al., 2000; Filella et al., 1995; Schlemmer et al., 2005).

Several laboratories (direct) and remote sensing (indirect) methods have been developed for estimating chlorophyll content of plants. The indirect methods, traditionally, destructive sampling is used for *in situ* collection of data from the field which is then analysed in the laboratory (Brix, 1987). This method is costly, labour intensive and destructive (Cortazar et al.,2015). Moreover, this method has been criticized for its very limited spatial coverage and also not applicable for large-scale estimation of chlorophyll. Alternatively, to overcome the problems associated with *in situ* based chlorophyll estimation, scientists have developed different remote sensing based (indirect) chlorophyll estimation techniques that are quick, non-destructive, efficient and have broader spatial and temporal coverage (Homolová et al., 2013). Remote sensing based chlorophyll estimation has been increased widely in the last decades(Hernández-Clemente et al., 2012; Kokaly et al.,2009). Likewise, remote sensing allows a simple representation of objects through their unique spectral signature in their electromagnetic spectrum (EM), hence can give accurate information about various vegetation variables being investigated (Liang, 2004). The visible, near infrared, shortwave and thermal infrared regions are depicted as useful regions for studying vegetation parameters (i.e. at the canopy and leaf level) (Kokaly et al., 2009; Rivera et al., 2014; Ullah, 2013; Yoder & Pettigrew-Crosby, 1995). In this regard, many researchers have confirmed the usability of remote sensing data at visible and red edge region for chlorophyll estimation (Daughtry et al., 2000; Darvishazdeh et al., 2008; Gitelson et al., 1996; Haboudane et al., 2002; Schlerf et al., 2010; Zarco-Tejada et al., 2002).

The technological advancement in the last century has boosted the availability and the usability of various high resolution multispectral remote sensing data which are useful for vegetation studies including chlorophyll content (Thenkabail, 2015). Some of the commonly used multispectral broadband satellite imagery for vegetation mapping and monitoring are LANDSAT, MODIS, SPOT, IKONOS, RapidEye, QuickBird, Sentinel-2, Proba-CHRIS, and Worldview-2. These satellites are known for their high spatial and temporal resolutions and also have wider applicability for estimation vegetation biochemical parameters. For example, Govender et al.(2008), reviewed Proba-CHRIS multispectral imagery for mapping and was able to differentiate different vegetation types using the reflectance data collected from vegetation surfaces. Similarly, Weber et al.(2006) used a high-resolution multispectral sensor (SPOT) for vegetation study and proved the potential of multispectral imagery for obtaining information from vegetation surface as equal as hyperspectral data. Moreover, previous studies had shown the potential of several multispectral satellite data for estimating leaf biochemical parameters such as chlorophyll content (Berni et al., 2009; Clevers & Gitelson, 2013; Croft et al., 2015; Darvishzadeh et al., 2012). Recently developed multispectral satellites are designed with red edge channel useful for estimating chlorophyll content (Adelabu et al., 2014; Delegido et al., 2011). For instance, the red edge band in RapidEye and Sentinel -2 multispectral satellite sensors are situated without overlap with other bands which is useful for vegetation parameter estimation. Moreover, spectral data at Red edge region are sensitive to vegetation densities and hence can be used for estimation of leaf and canopy chlorophyll concentration(Cho et al.,2008).

The presence of variability in the canopy characteristics in the case of mixed forest can affect the spectral reflectance measured by using remote sensing. Forest stands characteristic such as plant density, plant architectures, leaf angle and leaf morphological features are among the most important factors hampering the reflectance measured from the vegetation surface(Ollinger, 2011). Furthermore, the level of chlorophyll in the leaf and canopy also influencing the reflectance measured by the sensor(Thenkabail et al., 2011).These changes in the vegetation reflectance can be detected mainly in the red, blue and green reflectance region (Zarco-Tejada et al., 2000). Hence, satellite sensors with high spatial and spectral characteristics are able to detect reflectance both at the canopy and leaf level more accurately. However, the selection of appropriate sensor types still remains a trade-off between the cost and the availability of the image data (Darvishzadeh et al.,2012; Govender et al., 2008). For example currently, hyperspectral data are costly and are also scanty in their availability. Hyperspectral data are criticised for their large number of spectral bands and the multi- collinearity (band redundancy) and dimensionality problem (Govender et al., 2008). Conversely, data from multispectral sensors are relatively easily available at considerable cost. In spite of selecting proper satellite imagery and data selection, there is also a need for selecting proper modelling approaches which are robust in handling the multitude factors affecting the spectral reflectance under complex ecosystem conditions.

For retrieval of vegetation parameters from remote sensing data, generally, two types of modelling approaches have been employed. This include physical based radiative transfer models (RTM) and/ empirical models which are among the commonly applicable approaches for retrieving vegetation parameter (Liang, 2004). The radiative transfer models are assumed to be powerful models in retrieving vegetation parameters such as chlorophyll content (Demarez & Gastellu-Etchegorry,2000; Iaquinta et al.,1997). These models allow the establishment of a direct link between the vegetation parameters (leaf and canopy parameters), with the atmosphere and sensor through the principles of physical laws (Liang, 2004). Moreover, the results obtained from physical based radiative transfer mode(RTM) can also be easily transferable to another area (Darvishzadeh, 2008; Demarez & Gastellu-Etchegorry, 2000). However, for the successful retrieval of vegetation parameters using the physically based models from remote sensing data, the models have to be inverted using different inversion algorisms (Liang,2004). One of the commonly used methods for inverting RTM is through the use of Lookup table (LUT). Therefore, considering the overall advantage of physical model this study has employed an invertible forest reflectance model (INFORM)(Atzberger, 2000), high resolution multispectral image(i.e. RapidEye)(Weichelt et al., 2009; Shang et al., 2015) and look up table inversion approach(Darvishzadeh et al., 2012) to model leaf chlorophyll in Bavaria Forest National Park.

1.2. Problem Statement

The use of remote sensing technology in the last fifty years has been increasing for vegetation study and is also continuing in playing a paramount role in monitoring vegetation and land surfaces properties (Thenkabail, 2015). Remote sensing based plant biochemical estimation such as chlorophyll content has become more operational and extensively been utilized as compared to the existing traditional methods i.e. *in situ* based vegetation parameter estimation. Remote sensing based measurements of chlorophyll content are assumed to be relatively stable and provide a repetitive collection of data at local and global scale (Cohen et al.,2003; Liang, 2005).

Likewise, the recent development of new generation high resolution multispectral sensors such as RapidEye (Schuster et al., 2012; Zillmann et al., 2015) and Sentinel- 2 (Drusch et al.,2012) which have red edge spectral bands have created the chance of monitoring biophysical and biochemical parameters from any vegetation surfaces at different spatial and temporal scales. The red edge region available in these satellite shown to be sensitive to the different level of chlorophyll pigments and is useful for estimating chlorophyll content

A review of the literature revealed that the previous studies on chlorophyll estimation are mainly implementing data derived from the hyperspectral sensors. Given the existing potential application of multispectral imagery for vegetation studies, yet, most of the existing modelling studies for chlorophyll estimation are focusing in utilizing hyperspectral data with the statistical approach and or use physical base model. Indeed, broadband multispectral sensors are more frequently available and are less costly. Given this reality, limited research works were reviewed in this study that use of multispectral imagery for chlorophyll estimation applied to physically based model. Moreover, to our knowledge, the selected RTM model for this study (INFORM) is not well tested for retrieving chlorophyll content for heterogeneous ecosystem condition. Furthermore, limited research has been done on comparing different LUT generation approaches for retrieving plant biochemical components such as chlorophyll content. However, it has been suggested that the use of different LUT approaches have considerable impact on the accuracy of vegetation parameter retrieval. Therefore, this study aims to utilize high-resolution multispectral data with physically based INFORM RTM for modelling biochemical parameters in the forest (in this case foliar chlorophyll content) and look-up table (LUT) inversion approach.

1.3. Overall objective

The main objective of this study is to evaluate the use of high-resolution multispectral data with INFORM radiative model for modelling leaf chlorophyll content in the heterogeneous forest of Bavarian Forest National Park (BFNP).

1.3.1. Specific objectives

- To estimate leaf chlorophyll content by inversion of INFORM radiative transfer model using Look up table approach (LUT) in BFNP
- To evaluate the potential of high-resolution multispectral satellite imagery (RapidEye) for estimating leaf chlorophyll content using INFORM
- To identify the suitable bands in RapidEye image for leaf chlorophyll estimation

1.3.2. Research questions

- Does the LUT generation approach affect the retrieval accuracy of leaf chlorophyll content in BFNP? Which approach of LUT generation, for inversion of INFORM, will provide a more accurate estimate of leaf chlorophyll content in BFNP?
- What are the advantages and disadvantages of utilizing high-resolution multispectral imagery (in particular RapidEye) for estimating chlorophyll content?
- Which bands are recognized suitable for higher retrieval accuracy of leaf chlorophyll in terms of RMSE and R^2?

1.3.3. Hypothesis

- Inversion of the INFORM radiative transfer model using a randomly generated lookup table will provide an accurate estimate (In terms of R^2 and RMSE) of leaf chlorophyll content (in comparison to systematically generated LUT).
- Utilization of the red-edge band of (RapidEye imagery) during inversion of INFORM model will significantly increase the retrieval accuracy of leaf chlorophyll content in BFNP.
- Using the combination of all bands will provide higher retrieval accuracy for leaf chlorophyll in BFNP.

2. LITERATURE REVIEW

2.1. Overview of forest covers in the World and Europe

Approximately over 4 billion acres of land in the world(31%) is covered by the forest(accounting 0.6 ha of forest per capita), and these forests have great potential for storing a million tons of carbon (FAO, 2010). It has been suggested that of these most primary forest distributed in the world are mainly situated in inside protected areas. Legally established national parks, game reserves and others biodiversity hotspot areas are among the mentioned protected areas accounted for protecting such a huge amount of forested areas (FAO, 2010). Worldwide those vast amounts of forest are also located in Europe (FAO, 2011). According to European Commission Environment(2015), nearly 42% of the total EU land is covered by forest and other wooded vegetation. Various economic, environmental and social services have been derived from this forest biome by the peoples living in and the surrounding. The majority of the forests located in EU are characterised with mixed deciduous and conifers trees species typically dominated by beach, douglas, oak, maple, birch and spruce tree species(Perzanowski & Szwagrzyk, 2000).

Bavarian Forest National Park is among the major protected forest ecosystem found in southeastern Germany characterised with mixed forest ecosystem (Rall et al., 2008). The forest is known for provision wider economic, social and environmental benefit. Several study done on this forest revealed that the forest condition of the Bavarian has been frequent been affected by the disease (bark beetle) (Fahse & Heurich, 2011; Lausch et al., 2013). Therefore, a detailed study on the different vegetation parameters of this forest is required for efficient monitoring and implementation of a more accurate forest management plan/strategy. So far different research have been done in this forest and most of the research were focusing on the estimation canopy structural parameters and leaf traits (Ali et al., 2016; Ali et al., 2015), and leaf nitrogen (Z. Wang et al., 2015). Given the importance of chlorophyll pigments for monitoring plant health and the fact that this forest ecosystem has been frequently affected by forest disease (bark beetle) less has been studied about the chlorophyll level of the area using remote sensing.

2.2. Remote sensing of leaf biochemical

Leaf foliar biochemical parameters made from both pigments and non-pigment components can be easily represented through optical satellite sensors(Kokaly et al.,2009). Hence, the influence of these parameters on the leaf reflectance properties can be easily represented using data derived from this satellite mainly in the visible and near infrared region (Daughtry et al., 2000; Schlemmer et al., 2005). Sims & Gamon(2002) and Curran(1989) studied the concentration of different foliar biochemical components from the reflectance and transmittance data obtained at leaves and canopy level and able to predict their variability in space and time. Of those studied biochemical parameters chlorophyll (*a* + *b*), leaf structure, lignin, cellulose, nitrogen and water content are among some which can be easily detected by the optical sensor.

Chlorophyll pigments absorb a tremendous amount of red and blue colour in the spectrum of light radiated from the sun particularly in the visible part of the electromagnetic spectrum. Chlorophyll *a* has an absorption peak mainly located at the wavelength of 430nm and 662nm while chlorophyll *b* absorption peak is located at 453nm and 642nm wavelength and their estimation of relatives concentration can be done using reflectance mainly in this depicted region (Curran, 2001; Datt, 1999). Useful bands important for chlorophyll estimation were suggested(Carter & Spiering, 2000). Furthermore, Datt(1999) identified the reflectance around near 710nm (i.e. the red edge band region) as the most sensitive bands to a different level of chlorophyll pigments which is useful for estimation. Conversely, the wavelengths situated in the infrared regions are mainly affected by the water and other biochemical components and thereby identified as less useful wavelength regions for chlorophyll estimation. This difference was attributed due to the fact that in near infrared region the reflectance is mainly affected by the leaf structure and density of the vegetation whereas in the visible region the main governing factors affecting the reflectance are mainly the pigment concentration like chlorophyll and carotenoids(Gitelson et al.,2003). Consequently, using remote sensing and earth observation data this unique leaf spectral property can possibly be quantified and used for supporting any vegetation studies such as for monitoring and detecting plant phenological and physiological changes at different spatial and temporal scale(Thenkabail, 2015).

Figure 1shown below depict the wavelength range of reflectance spectrum from healthy plants which are categorised into three main regions visible (400-700nm) the dominant region were leaf chlorophyll effect can be visualized, near infra-red (NIR) (701-1300nm) and mid- infrared (1301 -2500nm). Indeed, any studies related to vegetation parameter reflectance be it biochemical and/or biophysical parameters are focused in those regions (Cracknell et al., 2009).

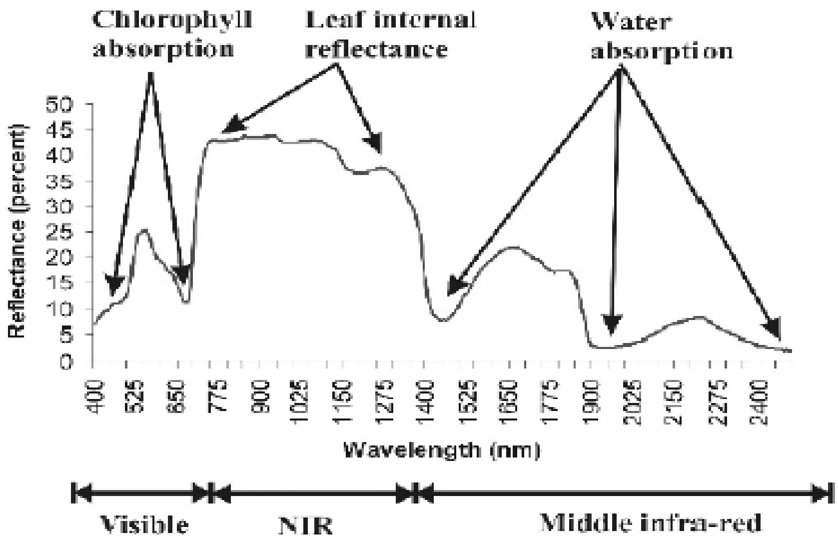


Figure 1: Typical leaf reflectance spectrum derived from vegetation.

Adapted from (Cracknell et al., 2009).

2.3. The red edge bands for chlorophyll estimation

The use of Red Edge region in vegetation parameter studies was been explored by different remote sensing researcher for many years for forestry and agricultural purposes (Weichelt et al.,2009). The Red edge region is the sharp slope between the visible (red absorbance)and Near -Infrared(NIR) reflectance region located around a wavelength of 680-780nm in vegetation spectra(Dawson & Curran, 199). It is the region at which the first spectral difference reaches local maxima and able in providing additional information for retrieving and detecting tree species, plant health condition, and density (Weichelt et al., 2009). The red edge region is more sensitive to leaf parameters such as chlorophyll content(Clevers et al.,2000). The region of the red edge channel was identified as the most important region which can be utilized for leaf chlorophyll estimation(Delegido et al.,2011). Rock et al.(1988) and Filella & Penuelas.(1994) analyzed the shifting position in red edge bands and used for studying leaf chlorophyll variability in time and space. The nonresponsive nature of the red edge band channel to the variation in soil background reflectance and atmospheric conditions made this region useful for estimation chlorophyll content(Clevers et al.,2000). In RapidEye band setting this band region(channel) is located without overlap with other existing bands(Weichelt et al., 2009).

Many researchers, for example; Cho et al.(2008b); Clevers & Gitelson.(2012,2013); Clevers et al. (2002,2001); Curran et al. (1995); Dawson & Curran. (1998); Gitelson et al. (1996) and Weichelt et al. (2009) investigated the importance of red edge bands and its derivative for estimating chlorophyll content. Delegido et al. (2011) have found chlorophyll estimation accuracy of r2=60% by utilizing the red edge bands in sentinel-2 satellite image. In the same work estimation of chlorophyll done without red edge band was shown to be less accurate. Schuster et al.(2012) tested the use of red edge band for land use classification and found an improved accuracy when the red edge band information was added to the analysis particularly for the forested area. A direct strong relationship between red edge position and total leaf chlorophyll content was investigated by (Clevers, 1994; Curran et al., 1991; Lichtenthaler et al., 1996). Nevertheless, limited research works were done that use of red edge band found in high-resolution multispectral satellite imagery such as RapidEye data for chlorophyll estimation. Therefore, in this research, we evaluated the importance of red edge bands in RapidEye satellite image for estimating leaf chlorophyll content using a physically based RTM model such as INFORM and LUT inversion approach.

2.4. Methods applied for vegetation parameter estimation: Empirical Vs Physical methods

The commonly existing model types used for vegetation parameter estimation from remote sensing data employ physically based model and empirical (statistical) models or the combined form of these models. The empirical model is commonly applied to large-scale forest inventories and also require a large set of collected data to establish a strong statistical relationship between parameters of interest and remote sensing data (Stenberg et al., 2008). Empirical(statistical approaches)are characterized by high uncertainties and are not robust when they are applied to environmental situations different than they are being developed (Verrelst et al.,2010). Moreover, empirical models are also criticized during upscaling from leaf to canopy process. Furthermore, an empirical model is sensitive to any varying canopy features, atmospheric and solar viewing angle (Verrelst et al.,2008).Vegetation indices(VI) are one of the commonly used empirical (statistical) approaches. This method is mainly dependent on species, sensor and sites and requires careful calibration (Zhang et al., 2008). Conversely, physical base models are more capable in handling any problem associated with the empirical model and can be applied to wider scale and situations.

Physically-based models are operating under the general principle of physical laws useful for retrieving vegetation biochemical parameter. This method allows an establishment strong linkage between vegetation variables(leaf and canopy variables) with remote sensing data through their spectral signal(Stenberg et al., 2008). Physical base models are robust in handling various environmental factors affecting the accuracy of vegetation parameters retrieval under a broader array of land covers types and sensor configurations(Iaquinta et al.,1997; Liang, 2004; Zheng & Moskal, 2009). The output from this model can be transferable to another study area with different environmental conditions (Liang,2004). Physically based model has to be inverted from simulated spectra generated for accurate vegetation biochemical parameters retrieval(Liang,2004). Radiative transfer models (RTM) are the commonly existing physical base model used for vegetation parameter quantification.

2.5. Radiative transfer model

Plant canopy reflectance can be influenced by numerous factors like canopy structure, illumination geometry, and soil background. This variation is mainly aggravated by the presence of ecosystem heterogeneity hence hampering the interaction of incident radiation between the vegetation surface and remotely placed sensor (Ollinger, 2011). The variation in the leaf reflectance was linked with the change in species types, composition, and plant developmental stages(Gitelson & Merzlyak,1996). Moreover, the difference in the background reflectance and LAI were also identified as main factors influencing canopy reflectance(Daughtry et al., 2000). However; these multitude factors influencing canopy reflectance can be resolved through the use of appropriate model type which is efficient in handling such complexities.

Radiative transfers models functioning based on radiative transfer equation are among the commonly used physical based model used for simulating spectral reflectance from any vegetation surface(Liang, 2004). Demarez & Gastellu-Etchegorry(2000) , demonstrated the usefulness of 3D physically based RT model for accurately retrieving canopy parameters under complex forest stand. Furthermore, coupled canopy model, as described in Daughtry et al. (2000) are another version of radiative transfer model suitable for handling reflectance invariant related to vegetation heterogeneity. However, physical models are also criticized for their ill-posed nature in which the different input parameter combinations give the same output. Combal et al.(2003) proposed the integration of prior information collected from the field during model parameterization as a solution to solve problems associated with ill-posed nature of physical base RT model.

Canopy RT model assume canopy as a turbid medium surface where the scattering and absorption by each individual leaf are assumed to be random. The major division of these model types as described by remote sensing researchers are categorized as , Monte-Carlo ray tracing models, Discrete Anisotropic Radiative Transfer(DART), hybrid model (for forests or sparse canopies), and radiosity model, geometrical-optical model(used for heterogeneous canopies) are among some of the RTM applied to simulate reflectance at canopy level (Dorigo et al., 2007; Widlowski et al., 2007).

Several physical base radiative transfer models have been implemented for retrieving vegetation biochemical and biophysical including chlorophyll content using the reflectance measured from leaf or canopy surface. For instance, Jacquemoud et al.(2000) evaluated the efficiency of four canopy and leaf level radiative transfer models for simulating corn and soybean canopy reflectance. SAIL canopy model (Verhoef, 1984) , PROSPECT a leaf optical model (Jacquemoud & Baret, 1990) for retrieve vegetation parameter at leaf level, PROSAIL the combined form of PROSPECT+SAIL model developed by (Jacquemoud et al., 2009) used for retrieving leaf and canopy parameters, LIBERTY model (Dawson et al., 1998) applied to conifers leaves are among the few physical based radiative transfer model which can be used for retrieving plant traits like chlorophyll. Furthermore, N-K canopy reflectance model developed by (Kuusk, 1995) also designed to address variation attributed from the single leaf bidirectional reflectance scattering problem under complex canopy structures. Schlerf et al. (2007) evaluated three canopy reflectance models such as SLC, FRT and INFORM used to represent canopy reflectance from vegetation surface. All the mentioned models have the efficacy in linking reflectance and transmittances measured by the sensor from the vegetation surface and are able to retrieve chlorophyll content both at leaf and canopy level.

2.6. RT Model inversion

For an efficient and accurate retrieval of biochemical parameters different models were been utilizing various inversion algorithm. Some of the most commonly used inversion algorithm applied to physical based models are Look up table approach(LUT) (Combal et al., 2003), artificial neural network (ANN) (Schlerf & Atzberger, 2006) and numerical optimization approaches (Kimes, et al., 2000). Likewise, these algorithms can be applied to pixel based retrieval of vegetation parameters including chlorophyll content. Besides the stated advantage, those mentioned methods have their own drawback. For instance, a numerical optimization approach is computationally intensive when applied to complex RTM and not appropriate for large data set hence optimal inversion might not be easily achieved. Furthermore, ANN requires proper training for fully establishing a strong relationship between the canopy variables and their respective reflectance. On the other side, LUT inversion algorism is assumed to be the simplest methods to construct and implement the inversion process. More interestingly, LUT method is also powerful in handling any arbitrary input set of parameters and also computationally fast as compared to numerical optimization approach for retrieving vegetation parameters from satellite data (Kimes et al., 2000). Furthermore, LUT approach allows the generation of the database by running the model in the forward mode as many times as possible to generate canopy reflectance based on the predefined range of input parameters and then the best fit bidirectional reflectance data can be obtained during the inversion process (Dorigo et al., 2007). He et al.(2012) in their study investigated different LUT size and parameter distribution effect on vegetation parameter estimation and they found that the LUT size and parameter distribution are the main factors which affect the accuracy of parameter estimation which needs care during the LUT generation. Further research on LUT was done by Darvishzadeh et al.(2012), considering different solutions(cases) and LUT size for estimating chlorophyll on rice from multispectral data.

2.7. Multispectral imagery for chlorophyll estimation

For proper implementation of precision forest management strategy, remote sensing has unlimited services. For instance Hernández-Clemente et al.(2012)demonstrated the usefulness of high-resolution multispectral data for extracting leaf biochemical parameter in the heterogeneous forest for assessing vegetation health. Curran et al.(2001) also suggested multispectral satellite images application for detecting and quantifying land surface information, particularly from vegetation canopy. Further research has also proved the usability of multispectral data for detection plant stress mainly using the reflectance collected from plant leaf and canopy hence be able to link with chlorophyll content(Trenholm et al.,2000). Similarly, many other research works have investigated the potential of multispectral imagery for quantitative estimation of vegetation biochemical at different spatial and temporal scale.

The list of literature review in which multispectral data used mainly for chlorophyll estimation on different vegetation and ecosystem types are depicted as follow : on rice crop using AVNIR 2 ALOS data (Darvishzadeh et al, 2012), barely, wheat and maize using SPOT data (Houborg & Boegh, 2008), on winter wheat using RapidEye data(Zillmann et al., 2015), on different agricultural crops and landscapes using simulated Sentinel-2 (Delegido et al., 2011; Verrelst et al, 2013) ,on wheat field using ATM data(Kurz et al., 2002), on different landscape of crop and grassland using SPOT data (Boegh et al., 2013), on cereal crop using RapidEye data(Perry et al., 2012) and on maize crops CIR image (Reum & Zhang, 2007), on field-grown spinach plants using GreenSeeker(TM) sensor(Jones et al., 2007), corn using SPOT-5 data (Houborg et al.,2009) and using Landsat Thematic Mapper (TM)(Daughtry et al., 2000), on mangrove forest using Landsat 8(Pastor-Guzman et al., 2015) and on oats crop using AggieAir imagery(Elarab et al., 2015). Likewise, multispectral data has also been used for chlorophyll estimation in forest for instance; on different tree species using Landsat data and simulated Landsat bands(Croft et al., 2015), on different broadleaf and conifers trees using Terra and Aqua MODIS data (Houborg et al., 2007),on oaks, beech, pines trees using SPOT and IKONOS data (Gascon et al.,2004)are some of the reviewed literatures in this study which are mainly focused on plant biochemical parameter retrieval using data derived from multispectral sensor and simulated data. Though a number of multispectral imagery are being used for estimation chlorophyll content still there are limited researches were done related to multispectral data application in estimating chlorophyll in forest. This might be due to the complex nature of the forest ecosystem as compared to other types of ecosystem and this demand proper image choice which is capable of addressing such complexity.

3. RESEARCH MATERIALS AND METHODS

3.1. Study area

The study was conducted in the Bavarian Forest National Park (BFNP) situated at (49° 3' 19" N, 13° 12' 9" E) of South -Eastern Germany along the border with the Czech Republic. The altitude of the area is ranging from 600m to 1473m above sea level, generally, the area is considered mountainous. The total area covered by the park is 24 218ha. The area is characterized by a temperate climate. The lowest average annual temperature of the study area was found 3 to 6 degree Celsius during the summer and heavy snow cover during the winter. The dominant soil types are Brown soil, loose brown soil and podzol brown soils and are widely distributed in different altitudinal ranges. Generally, these soils are characterized as acidic and low in nutrients content primarily consists of genesis and granite parent material (Ali et al., 2015; Heurich et al., 2010).

The forest ecosystem is characterized as mixed mountain natural forest and varies with altitude in which alluvial spruce forests dominated in the valleys and spruce forests in the hillsides and mountain areas. The dominant trees species are Norway spruce (*Picea abies*) ~67%, Fir (*Abies alba*) ~2.6 and European beech trees (*Fagus sylvatica*) ~ 24.5% mainly in the sub-montane parts. Besides these trees species, there are also other tree species associated with such as mountain ash *(Sorbusaucuparia*)~ 3.1%, sycamore maple(*Acer pseudoplatanus*)~1.2%, Goat willow(*Salix camera*) and birches trees species found as mixed forest(Heurich et al., 2010; Kautz et al.,2011).

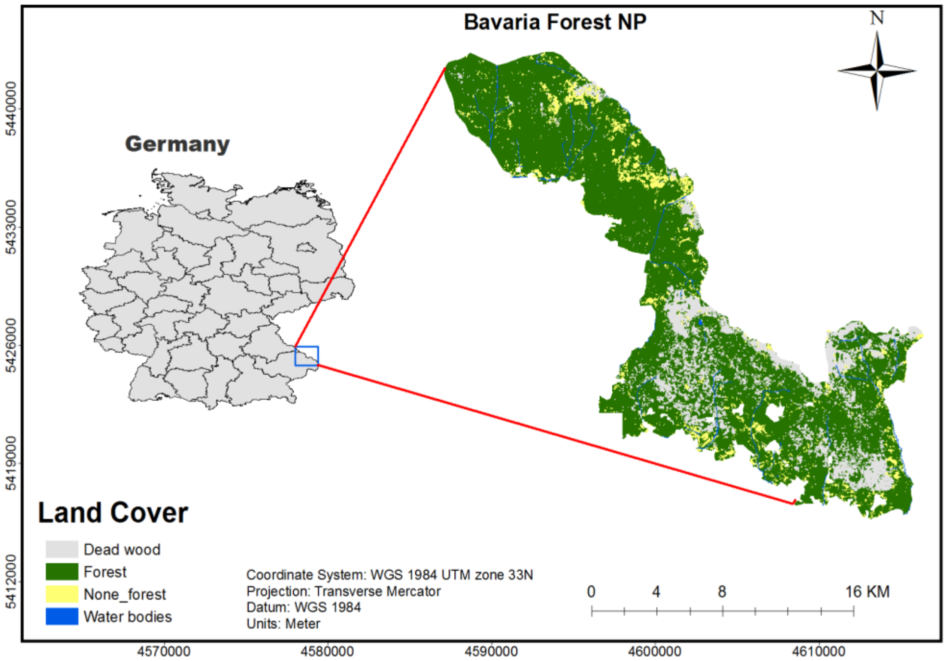


Figure 2: Location of the study area in the Bavarian Forest National Park (BFNP), Germany.

The source of the shape file for Germany was obtained from (http://www.diva-gis.org/datadown).

The forest is characterized by having a long history of bark beetle attack (*Ips typographus*) and this has resulted in a massive proliferation of conifers species like spruce trees leading to a death of 6000ha (Lausch et al., 2013). Figure 2 also show the area covered by the dead tree as a result of such catastrophe.

3.2. Materials

Field measurements

The main objective of collecting ground data was to obtain the most valuable information's which are representative to the actual situation of the forest ecosystem being investigated and to use them during model parameterization. Chlorophyll ground data was also used for validation of the chlorophyll retrieved by the model.

3.2.1. Sampling design and data collection

The ground truth data on different forest structural variables were collected during the field campaign in July 2015 by staff and Ph.D. students of Natural Resource Department, Faculty of ITC, University of Twente. To facilitate the data collection, the study area was first stratified into the forested and none forested areas using the available land cover map. Following this, a total of 40 sample plots with the sizes of 30m x 30m were randomly established in the forested area. The distributions of sample plots are presented in Figure 3.

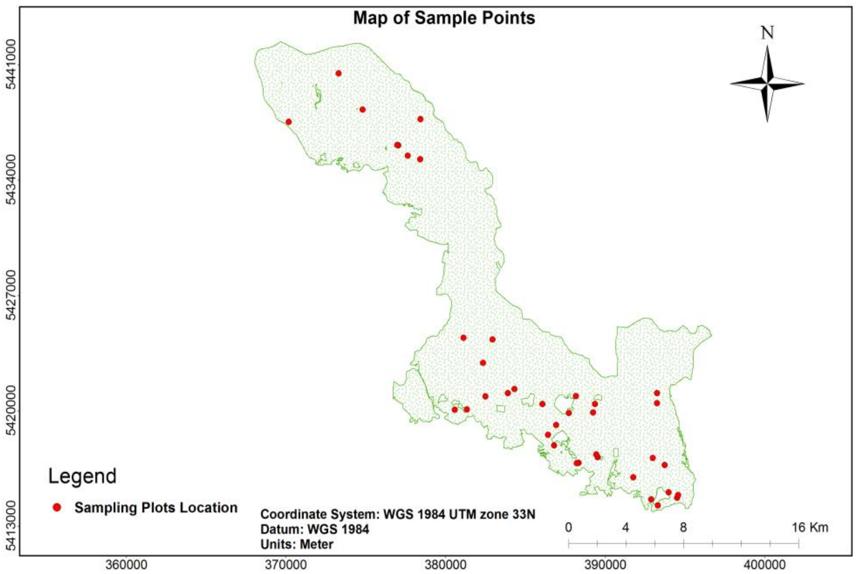


Figure 3: The distribution of sample plots in the study area shown in red dots

The central location of the sample plots were determined by using the Garmin Oregon 550T GPS with an accuracy of +/- 4 meter. In each sample plot different biophysical parameters such as tree height, canopy diameter, LAI, steam density, and average leaf angle were recorded. To obtain the biochemical properties such as chlorophyll, within each plot 4-5 trees were randomly selected and the leaf samples were collected using Excalibur Matrix 310 Crossbow from the top canopy layers. Then sampled leaves were instantly sealed into zip-lock plastic bags and kept in a cooler with ice till they are transported to the laboratory for subsequent chemical analysis. To increase the accuracy of chlorophyll extraction from the leaf and obtain a representative output, a multiple leaf samples were collected from each plot and then averaged to get the leaf chlorophyll content at the plot level. The summary statistics of the measured forest structural variables are given in the Table 1.

Table 1: summary statistics of field and laboratory measured forest biochemical and physical parameters

Basic statistics	Height	CD	ALA	LAI	Steam /ha
Minimum	14	1.5	28.29	0.505	189
Maximum	29	8	64.61	5.86	500
Mean	19.93	4.12	47.28	3.414	307
Std.dev	3.64	1.53	8.31	1.06	79

3.2.2. Laboratory chlorophyll measurement

The laboratory analysis was done at ITC geoscience laboratory. A sample of 0.5g leaf was prepared first and weighed using a digital measuring balance. Then the leaf were grounded about 5-minutes using mortar and pestle by adding 3ml of pure acetone(100%) which facilitate the process of maceration, until the pulp get turned into white colour and all the green pigments extracted. The extracted chlorophyll was transferred to test tubes and then to get the required amount of solution, 7ml of pure acetone was added to the extracted sample. To facilitate the mixing up of acetone with the extracted chlorophyll and finally to make the extract fully transparent during spectrophotometer reading the samples were placed in the centrifuge for 4-5 minutes at 4000rpm. The extraction was done based on the empirical formula given by(Lichtenthaler & Buschmann, 2001).

The spectral absorption measurement of chlorophyll was done by using UV 6300pc spectrophotometer (VWR International, 2015). Before taking the actual chlorophyll measurement first, the UVs instrument was calibrated using the 100% pure acetone reference sample through the basic mode configuration. The calibration was done for the whole range of wavelength from 190 to 1100nm. This was done to avoid any measurement error while scanning the actual samples. Then after immediately removing the samples from centrifuge a 2 ml sample of purely homogenized chlorophyll extract was prepared for measuring the chlorophyll absorptions. The absorption coefficients for Chl *a and b* measurement were done separately at selected chlorophyll sensitive wavelengths (λ) of 661.8nm and 644.8 at 0.1nm steps, respectively. To get the chlorophyll concentration of *a* and *b* in ug/ml, the equation by (Lichtenthaler & Buschmann, 2001) was adopted.
The calculation was done accordingly:

$$[Chla]\left[\frac{ug}{ml}\right] = 11.24 * A661.6 - 2.04 * A644.8 \text{---------------- (Eq.1)}$$

$$[Chlb]\left[\frac{ug}{ml}\right] = 20.13 * A644.8 - 4.19 * A661.6 \text{---------------- (Eq.2)}$$

Total Chlorophyll concentration was calculated as the sum of Chl a and Chl b:

$$[Chl\ total]\left[\frac{ug}{ml}\right] = [Chla] + [Chlb] \text{-----------------------------(Eq.3)}$$

Where *Chla*= chlorophyll a; *Chlb*= chlorophyll *b*; A=absorbance (the unit is dimensionless)

Figure 4: Laboratory sample preparation in Geoscience laboratory, Faculty ITC, and the instrument UV 6300pc spectrophotometer used for the chlorophyll measurements.

The laboratory measured chlorophyll concentration was converted into area based chlorophyll content (ug/cm^2) for each sample plots. The conversion was done based on the (http://www.aquacalc.com/convert/surface-density/milligram-per-square-centimeter)

3.2.2. Satellite Image

High-resolution multispectral satellite images of RapidEye were acquired on July 2/2015 parallel to the field campaign. The satellite is a single sun-synchronous orbit plane with an attitude of 630km. The orbital period combined with the phasing makes the satellite view the earth at any points during 24 hour period off nadir and 5.5 days at nadir (Anderson et al.,2013). It is a constellation of five satellites providing multispectral imagery in 5 bands (Table2). The orthorectified pixel size of the image is 5m (Anderson et al., 2013). The mosaicked image was prepared from four images covering the study area, since a single image was not able to cover the whole study area.

Table 2: Characteristics of RapidEye spectral bands

Nr.	Name	Start WL	Middle WL	End WL	Sp.Rg	Spat.Res
1	Blue	440	475	510	70	5
2	Green	520	555	590	70	5
3	Red	630	657.5	685	55	5
4	Red edge	690	710	730	40	5
5	Near Infrared	760	805	850	90	5

Source: http://blackbridge.com/rapideye/

Angular characteristics obtained from the image Metadata acquired during acquisition period were calculated from the image. Hence, during the INFORM model parameterization, these external parameters associated with the sensors were set to their average value based on the information provided in Table 3.

Table 3: Sensor related information derived from the Metadata

Descriptions	Value	Representation
Average Scene incident angle	3.8125	Degree
Average illumination Azimuth angle	171	Degree
Average illumination elevation angle	64.075	Degree
Average space azimuth angle	102	Degree
average spaceCraftViewAngle	3.18	Degree
Projection type	na	Transfer Mercator
Coordinate system	na	WGS-84 –UTM zone 33

3.3. Methods

3.3.2. Image pre-processing

3.3.2.1. Image calibration to surface reflectance

In order to increase the usability and quality of information retrieved from the image and to be able to extract information accurately surface reflectance was calculated. The satellite images used for this study were obtained as level 3A product in which all the radiometric and geometric correction were applied by the provider

To calculate the Top Of Atmospheric (TOA) reflectance measured by the sensor, band Maths algorism in ENVI-IDL5.2 were utilized. The equation implemented for TOA normalization was adopted from (RapidEye, 2011) and was given as follow:

$$REF(i) = RAD(i) * \ (\pi * SunDist\hat{}2\ )/(EAI(i) * \cos(SolarZenith)\ ) \text{----------------- (Eq.4)}$$

Where

- I: the number of spectral bands
- REF: is the reflectance value at the TOA
- RAD: is the radiance value to which the image is calibrated or scaled (it is the product of DN* radiometric scale factor of the image)
- Sun Dist: Earth-Sun Distance at the day of acquisition in Astronomical Units (ranges between 0.9832898912AU to 1.0167103335AU)
- EAI: Exo- atmospheric irradiance
- Solar Zenith: Solar Zenith angle in degree (90-Sun elevation angle)

3.3.2.2. Image spectral reflectance extraction

Spectral reflectance was extracted from the pre-processed satellite images for the selected 40 sample plots. The GPS points collected during the field campaign were used as inputs in order to geo-locate the sample points properly hence facilitate the extraction. The spectral extraction was done in ENVI-IDL5.2 spectral analysis toolbox developed by the NRS. This toolbox requires only sample points (GPS) converted into shapefiles and the pre-processed image normalized into TOA reflectance value. The average spectral reflectance of each sample plot was extracted by applying the window size of 5*5 pixels (i.e. 25mx25m) in NRS spectrum toolbox. This window size was selected to avoid the error of geo-location of sample points. Furthermore, taking the value of the pixel located at the centre of the point (pixels) also allow us to avoid the plot border effects. Finally, the extracted image spectral reflectance of the plots, hereafter called measured reflectance, were used for further analysis and the lookup tables inversions. Figure5 shows the extracted reflectance from the image (measured reflectance) of the 40 sample plots.

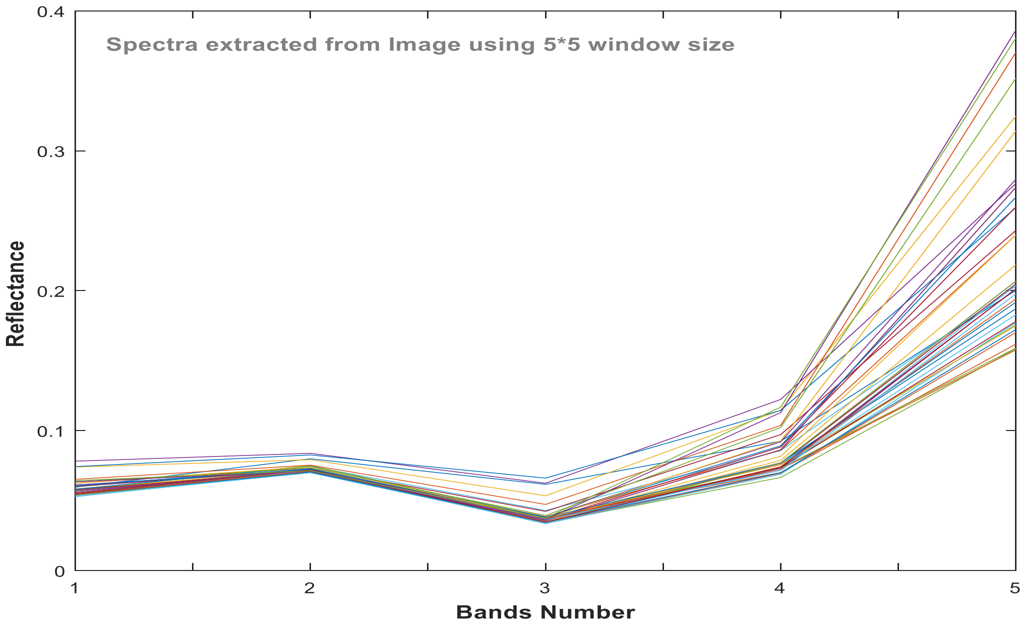


Figure 5: Reflectance of sample plots extracted from the mosaicked image using 5x5 pixels window size

3.4. INFORM radiative transfer model

Since the selected study area is characterized by heterogeneous forest, therefore, this demands a proper model selection that accounts these complex structures of the forest. As described by Demarez & Gastellu-Etchegorry(2000) coupled canopy models are assumed to be robust in handling such a complexity raised from ecosystem heterogeneity. Therefore, for this study an invertible forest reflectance model (INFORM) which is a type of an integrated canopy reflectance model developed by (Atzberger, 2000; Schlerf & Atzberger, 2006)was used for simulating canopy reflectance. The INFORM is a physically based canopy radiative transfer model, consisting of three sub models namely: forest light interaction FLIM model (Rosema et al., 1992), PROSPECT leaf model (Jacquemoud & Baret, 1990), and SAIL canopy model (Verhoef, 1984). The model was developed to simulate the canopy spectral and bidirectional reflectance in complex structure forest stands (Atzberger, 2000), that cannot be achieved through the use of 1D radiative transfer model. The INFORM was considered as suitable canopy model in linking the canopy variables with reflectance data. In INFORM, the forest is considered as discontinuous canopy layer with tree crown and gaps (Rosema et al., 1992).Therefore, in order to properly model the different input parameters first the INFORM submodels needs to be parameterized independently according to the input variables they are required.

3.4.1. Model Parameterization

INFORM model can be parameterized by leaf parameters such as Cm, Cw, N, and chlorophyll (*a+b*), canopy parameters such as SD, LAI, canopy cover percentage (CC%), canopy diameter (CD) and H (tree height) and then external parameters: sun zenith (θs) and sun azimuth angle (ψ), hence be able to simulate the forest canopy reflectance in the wavelength region between 400-2500nm. In the model to calculate the reflectance at the forest canopy the crown transmittance with the sun and observation direction, the crown reflectance at infinite crown depth and the background reflectance was computed from the SAIL, PROSPECT and FLIM RTM models. Some of the mathematical algorithms used to fix the input parameters for the model were explained in the next subsection.

Parameterizing the models with the inputs variables representing the local situations in which the model was being implemented is assumed to increase the success of parameters retrievals(Baret & Buis, 2008; Combal et al., 2002). During model simulation, the input parameters that did not have a strong effect on the canopy reflectance in the selected wavelengths have been fixed to their reasonable value ranges using either data obtained from the field (Table4) or earlier studies. The range for chlorophyll was set approximately close to the actual range measured in the field. The fixing of parameter's close to their actual measured values can also help in soliciting the ill-posed problem associated with the physical based radiative transfer models (Baret & Buis, 2008).

3.4.1.1. Parameterising leaf optical model: The PROSPECT

The PROSPECT leaf optical model is capable of simulating leaf hemispherical transmittance and reflectance (Jacquemoud & Baret, 1990). The modified version of leaf optical PROSPEC-4 was selected for this study. This model version is capable of simulating the leaf transmittance and reflectance properties in the range of 400-2500nm. PROSPECT-4 model input parameters are four including leaf structural and biochemical parameters such as leaf structure parameter (N) which is unit less, chlorophyll content (Cab) in ug/cm^2, leaf dry matter content (Cm) in ug/cm^2, and leaf water content (Cw) expressed in ug/cm^2 (Feret et al., 2008; Jacquemoud & Baret, 1990). The simulated leaf spectral transmittance (τleaf) and leaf spectral reflectance (ϱleaf) of overstory and understory vegetation from PROSPECT leaf model can be used as input to the INFORM model were calculated based on Jacquemoud & Baret.(1990)as:

$$\mathrm{leaf}(\tau, \rho) = \mathrm{fprospect}(\mathrm{N}, \mathrm{Cab}, \mathrm{Cm}, \mathrm{Cw}) \text{--- (Eq.5)}$$

In this study the leaf structure parameter (N) which is difficult to measure in the field was fixed to the recommended range value (1.5) in literature for the conifers trees in Ali et al. (2015) and Malenovský et al.(2006). The output of spectral properties from the simulated leaf by the PROSPECT model was used as input for the SAIL canopy model during the INFORM simulation (Atzberger, 2000).

3.4.1.2. Parameterizing canopy model: The SAIL and FLIM

The Scattering by Arbitrarily Inclined Leaves (SAIL) canopy model which is an integral part of INFORM model was adapted to estimate the bidirectional transmittance from the vegetation canopy (Verhoef, 1984). SAIL is a turbid medium canopy model which assume forest canopy as horizontally uniform parallel plane with many layers and the soil as diffuse reflector object. The main input parameter for this model are: the average leaf inclination angle (ALA (deg)), leaf are index (LAI (m^2m^{-2})) ;sung angle, (θs(deg)); observation angle (θo(deg)); the relative azimuth angle between sun(illumination) and sensor observation (ψ(deg)); the fraction of diffuse radiation (sky), soil parameters or background reflectance (rsl) and the hot spot parameter (hot(mm^{-1})).

The crown transmittance in the observation To and sun direction Ts (for any leaf transmittance τ and leaf reflectance ϱ) input used during INFORM model can be calculated from the SAIL model as follow: reference!

$$To = fSAIL(LAI, ALA, \tau, \rho, \theta o, \psi, skyl, hot) \text{----------------- (Eq.6)}$$
$$Ts = fSAIL(LAI, ALA, \tau, \rho, \theta s, \psi, skyl, hot) \text{----------------- (Eq.7)}$$

The value of the skyl was fixed to the default value of 0.1 as suggested by Darvishzadeh et al. (2008) and Schlerf & Atzberger.(2006). Furthermore, Clevers & Verhoef.(1993) suggested very limited or negligible overall influence of diffuse radiation (skyl) on the canopy reflectance is compared to other variables.

The FLIM model (Rosema et al.,1992) is another submodel integrated with INFORM canopy model and is used to simulate the reflectance from the forest stand (Rλ). Coupling this model in INFORM helps in resolving the shadow and transmittance effect originating from the forest structure(Schlerf & Atzberger, 2006). In FLIM the forest is considered as non-continuous layer and the reflectance can be calculated as:

$$R_\lambda = R_C.C + R_G.G \text{--- (Eq.8)}$$

Where Rc is crown reflectance at infinite depth and RG is the background reflectance (i.e. reflectance from the forest floor). Variables C and G are the crown and ground factors, respectively($C+G \leq 1$). The value of RG and RC were estimated using the SAIL model(Schlerf & Atzberger, 2006). Furthermore, external parameters (i.e. sensor related parameters) which are used as input to the model were calculated from the sensor Metadata. Finally, the simulation of reflectance from forest canopy was calculated in invertible forest canopy reflectance model (INFORM) taking all the output obtained from the three submodels. The forest canopy reflectance (R) in INFORM was calculated as:

$$\boldsymbol{R = fINFORM(SD, CD, H, LAI, ALA, LAIu, \rho soil, cab, N, cm, cw, \theta s, \theta o, \psi, skyl)} \textbf{ ----- (Eq.9)}$$

3.4.2. Model sensitivity analysis

Before running using the model and generation of LUTs, model sensitivity analysis was performed in order to understand the effect of different input parameters on the reflectance and also to investigate the robustness of the model to each parameter changes; hence fixing the less important parameters during the subsequent model simulations. Taking the recommendation from Bowyer et al.(2003), a local sensitivity analysis was performed to examine the influence of each input forest parameter on canopy reflectance in INFORM model. The local sensitivity analysis allows varying one parameter at a time during model simulation while other parameters are fixed at their average values. The analysis was done in Mathlab version 2015b. Prior to performing sensitivity analysis, first the different range values of the key inputs parameters were fixed to their range of minimum and maximum value obtained from field measurement (Tabe4). Thereafter, the effect of each parameter on the reflectance was investigated by varying the parameter value systematically in the selected wavelength region. For instance when sensitivity analysis is done for chlorophyll content (Cab), the value of chlorophyll is changing and all other parameters were kept constant at their average value. The range of wavelength in which the simulations were performed is based on the band configuration of RapidEye image ranging from 440nm to 850nm (Figure7).

3.4.3. Look Up table Inversion

The look-up table search was performed for retrieving chlorophyll content during INFORM simulation. Two types of look table namely randomly generated and systematically generated were built based on the input parameters set in Table4. During the parameter setting the prior information collected from field data were used to set the maximum and minimum values for each input parameter. The use of prior information was to avoid the ill-posed (Combal et al., 2003) and also was used to limit the size of the LUT.

The size of the LUT is the main issue that needs consideration during synthetic database generation (He et al., 2012; Weiss et al., 2000). Generating too big LUT size requires long time for processing and also it demands big space for storing the simulated data. Likewise, small LUT size has its own disadvantage(He et al., 2012). Small LUT have a nature of over generalization or smoothing and the output obtained for each inversion might not be the same or vary greatly especially for the randomly generated look-up table (Darvishzadeh et al., 2012; Weiss et al., 2000). Therefore, considering both the processing capacity of the computer and time required to simulate the data the optimal size of LUT was set as suggested in (Darvishzadeh et al., 2012; He et al., 2012). Finally, using the predetermined field and laboratory data the size of the LUT was set to be 150000 forest spectra for randomly generated LUT and 147744 forest spectra for systematically generated look-up table. The random LUT was generated only by fixing the upper and lower boundary of the input variables selected to vary during the simulation.

Table 4: Input parameters used for generating LUT during INFORM simulation

Variables	*Symbol*	*Unit*		*Min*	*Max*	*Constant*
Canopy parameters						
Crown diameter	CD	m		1.5	10	*
Steam density(stand density)	SD	n/ha		150	700	*
Stand height	H	m		13	30	*
Single trees LAI	LAI	m2·m−2		0.5	7	*
LAI understory	lAIu	NA	0.1			0.1
Average leaf angle of understory	ALAu	degree		40	80	*
Leaf parameters						
Leaf structure parameter)	N	NA	1.5			1.5
Chlorophyll content(a+b)	Cab	µg·cm−2		20	60	*
Leaf dry matter content	Cm	g·cm−2		0.0102	0.037	*
Equivalent water thickness	Cw	g•cm−2		0.006	0.035	*
External / sensor parameters						
Fraction of diffuse radiation	skyl	fraction	0.1			0.1
Scale		%	0.1			0.1
Azimuth angle	ψ	degree	171			171**
Sun zenith angle	θs	degree	26			26**
Observation zenith angle	θo	degree	0			Constant

The * shown in the table is indicating the variables varying during the whole modelling process. The ** star shows information derived from the image Metadata.

During the simulation, only eight parameters were allowed to vary and the other parameters were fixed at their mean value. The parameter selected to vary during the LUT generation were chosen based on the result obtained from the sensitivity analysis and prior knowledge.

To generate the systematic LUT, a forest canopy spectra with an approximate permutation of 3Cm x 3Cw x 16 Cab x 5LAI x 3 SD x 3H x 4CD x4ALA was used resulting in a LUT with the size of 147744 simulated spectra. The simulated data were stored in the LUT used for inversion. Finally to get the estimated leaf chlorophyll content and the reflectance value the best LUT search was done.

The best matched reflectance between the measured (Rmeas) and LUT simulated (Rlut) at each measured wavelength were obtained following the general principles of the cost function. This is basically used for finding the solution of the inverse problem obtained during LUT generation as described in (Atzberger et al., 2015; Darvishzadeh et al., 2012). The cost function allow us in calculating the RMSE with the least distance between the (Rlut) and (Rmeas) which later be used for chlorophyll estimation. The RMSE was calculated according to the equation 10.

$$RMSEr = \sqrt{\sum_{k=1}^{n} \frac{(Rmeasured\lambda - R\ lut\lambda)\text{expo2}}{n}} \quad \text{-------------------------- (Eq.10)}$$

Where R measured is indicating the measured reflectance from the image at a given wavelength, Rlut represents the simulated reflectance in the INFORM model at given wavelength and n represent the number of bands used during the simulation.

3.4.4. Model validation

The leaf chlorophyll content retrieved using the INFORM model was validated against the laboratory measured chlorophyll content. The laboratory measured chlorophyll was used as reference data for validating every chlorophyll data simulated in INFORM model. The accuracy of the validation result were presented in terms of coefficient of determinations (R^2), root mean square error (RMSE) and bias were calculated for each simulated canopy spectra and retrieved leaf chlorophyll content. Richter et al.(2012) suggested the use of these statistical measures for measuring the performance efficiency applied to vegetation parameter estimation models (physical base model).

3.4.5. Software's used

In order to process and analyse the data different software's were used in this research. Table 5 show the list of software's employed during the whole period of the research. Most of the chlorophyll retrieval and data analysis process were done in the Matlab Version 2015b software. The image analysis was done in ENVI 5.2, Arc Map 10.3.1, and ERDAS IMAGINE 2015. Besides this Microsoft excel also used for processing and analysis of the data. And click chart for drawing a flow chart.

Table 5: List of software's used

No	Type of instrument	Used for
1	ArcMap	mapping generating and GIS analysis
2	ENVI 5.2	spectral extraction
3	Matlab 2015b	LUT inversion and modelling, statistical data analysis
4	ERDAS IMAGINE 2015	Image analysis
5	Mircosoft Excell and R-studio	data exploration, processing and making graphs

3.4.6. General flow chart for research methods

The flow chart demonstrate the different research steps followed for achieving each proposed research objectives and associated research question. The overall research process consisting of, remote sensing data analysis, model parameterizing, and laboratory data processing are the starting point of the research. The second stage of the process was obtaining reflectance from remote sensing data and building a database (synthetic database) in the LUT and which latter was used as input to the inversion. The third step is model validation and accuracy assessment using different statistical analysis.

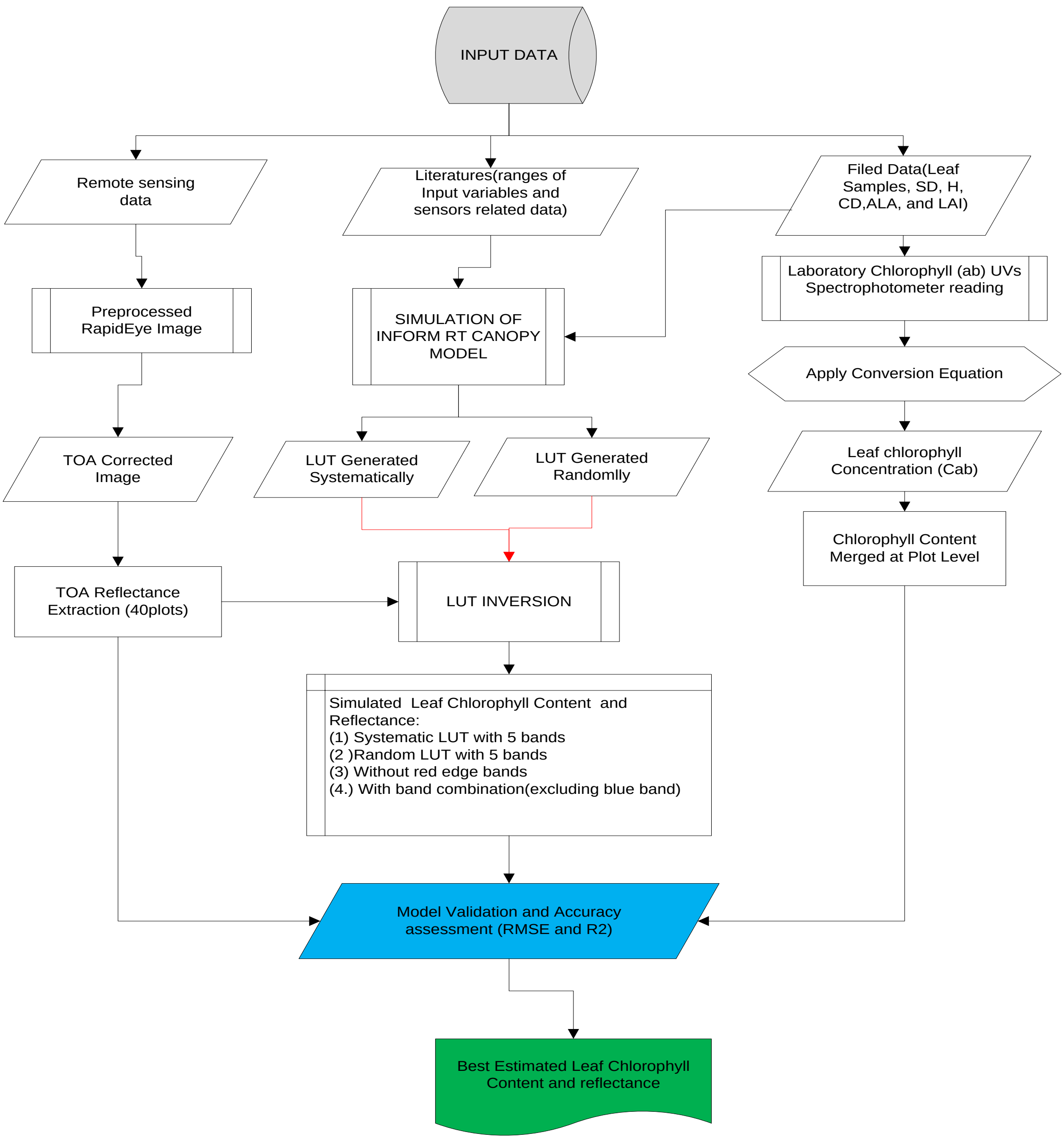


Figure 6: Methods flow chart.

In the box abbreviations letters represented are defined as LUT (look-up table), TOA (top of atmosphere reflectance), Cab (Chlorophyll *a* and *b*).SD (stand density), H (height), LAI (leaf area index), ALA (leaf angle), and CD (canopy diameter)

4. RESULT

4.1. Wet chemistry chlorophyll estimation

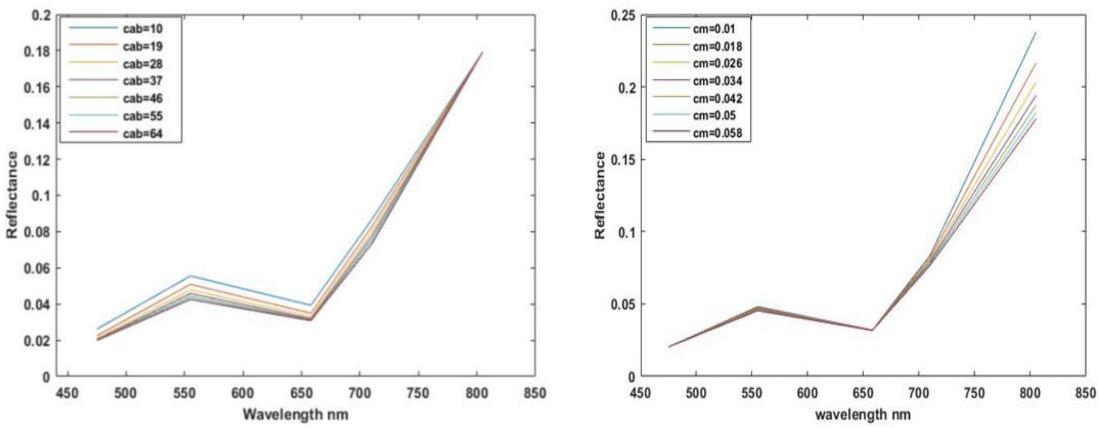
The leaf chlorophyll content obtained from the laboratory analysis is presented in table 6. The range of the chlorophyll content expressed in ug/cm^2 was found as 23.05 to 53.19ug/cm^2. Measured chlorophyll demonstrated a relatively high variation (Std=6.81).The range of chlorophyll obtained in this study is also in agreement with the range of chlorophyll content reported by (Wang et al., 2015).

Table 6 Summary statistics for leaf chlorophyll measurement obtained from wet chemistry analysis.

Basic statistics	Chlorophyll (ug/cm2)
Minimum	23.05
Maximum	53.19
Average	38.99
Standard dev.	6.81

4.2. Parameter sensitivity analysis

Sensitivity analyses (SA) were performed using INFORM in order to assess the importance of forest stand parameters influencing the canopy reflectance using the RapidEye wavelengths utilized in this study. Likewise, later throughout this study, the input parameters which were identified as the most influential during this step were varied during LUT inversion. Figure9 illustrate the influence of different forest stand structures and leaf parameters on the simulated canopy reflectance in RapidEye bands settings.



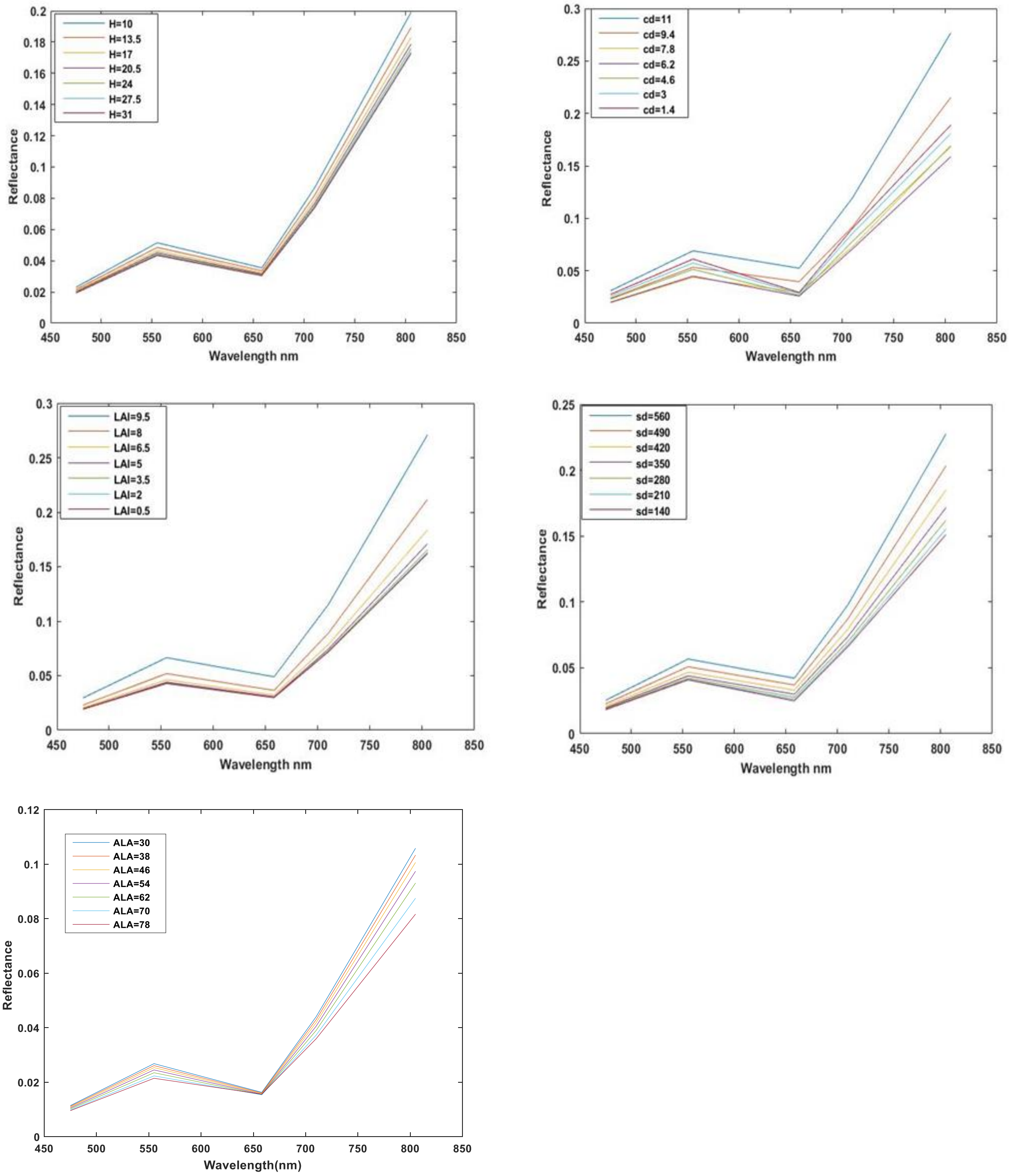


Figure 7: Sensitivity analysis using INFORM.

The effects of chlorophyll content(cab), dry matter content(cm), stand height(h), crown diameter(cd), leaf area index(LAI), steam density(sd) and average leaf angle(ala) on the simulated forest canopy reflectance spectra in 440 nm to 850 nm spectral region.

Chlorophyll a and b (Cab), dry matter content (Cm) and water content (Cw) were selected to vary during model simulation. These parameters were selected assuming that they have a significant impact on forest reflectance at canopy level.

As can be observed from Figure 7 forest structural variables such as leaf area index (LAI), stem density (SD), canopy diameter (CD), tree height (H), average leaf angle (ALA), were among the most important parameters identified during the sensitivity analysis as they had shown a strong effect on the canopy reflectance in the selected wavelength region (i.e. RapidEye wavelength region). It seems that the effect of these parameter on canopy reflectance are becoming more pronounced beyond the selected wavelength region (Figure7). The effect of non-pigment leaf element such as dry matter content (Cm) was noticeable around the shoulder of near infrared region approximately beyond 720nm (Figure 7). Conversely, this parameter has no effect on the wavelength less than ~720nm (visible range). The influence of leaf water content on canopy reflectance was not observed for the wavelength region selected for this study (i.e.440-850nm) (not shown). Finally, leaf chlorophyll (Cab) which is the focus of this study has shown significant impact on canopy reflectance in the wavelength region between 400-750nm. Furthermore, it was also observed that Cab has less/almost no effect on reflectance beyond the red edge region (~750nm wavelength range).

Consequently, considering the overall contribution of each forest parameter on canopy reflectance which was examined during SA, the following parameters SD, CD, LAI, H, ALA and Cab were allowed to vary at finer step during the entire LUT generation. Likewise, parameters like cm and cw which have a minor effect on canopy reflectance for the selected wavelength region have kept varying at wider range for the LUT generations.

4.3. The effect of LUT generation on leaf chlorophyll content retrieval

4.3.1. Chlorophyll retrieval using systematically generated LUT

The systematically generated LUT from INFORM radiative transfer model was utilized for the inversion process together with the measured reflectance in order to retrieve leaf chlorophyll content of the sample plots (N=40). The best match between the simulated reflectance (from LUT) and the measured reflectance was calculated using the LUT search algorithm based on the minimum RMSE criterion. The simulated reflectance which mostly resembled (with minimum RMSE) the measured reflectance of the plots were selected and the corresponding leaf chlorophyll contents were retrieved respectively. Finally to validate the model performance, the relationships between measured and retrieved leaf chlorophyll contents were evaluated using the RMSE and R^2 value. Based on this, the measured and estimated leaf chlorophyll content had a root means square error of (RMSE=13.18ug/cm^2) and coefficient of determination (R^2=25.48%). Likewise, the estimated relative root mean square error (rel. RMSE) and bias value were found to be 33.79% and 9.37, respectively. Figure 8 shows the scatter plot between the measured and estimated leaf chlorophyll contents obtained from systematically generated LUT. The range of leaf chlorophyll contents retrieved in this approach lie in the range of 20ug/cm^2 to 48.6ug/cm^2. The scatter plot shows the distribution of the points in 1:1 line. From the scatter plot, it was observed that the distributions of the sample points are concentrated to the lower boundary of the 1:1 line, indicating the underestimation of leaf chlorophyll content. This is particularly the case for the measured leaf chlorophyll values of 30 to 45ug/cm^2. This underestimation might be explained by the ill-posed nature of the physical model in which different input parameters resulting similar outputs.

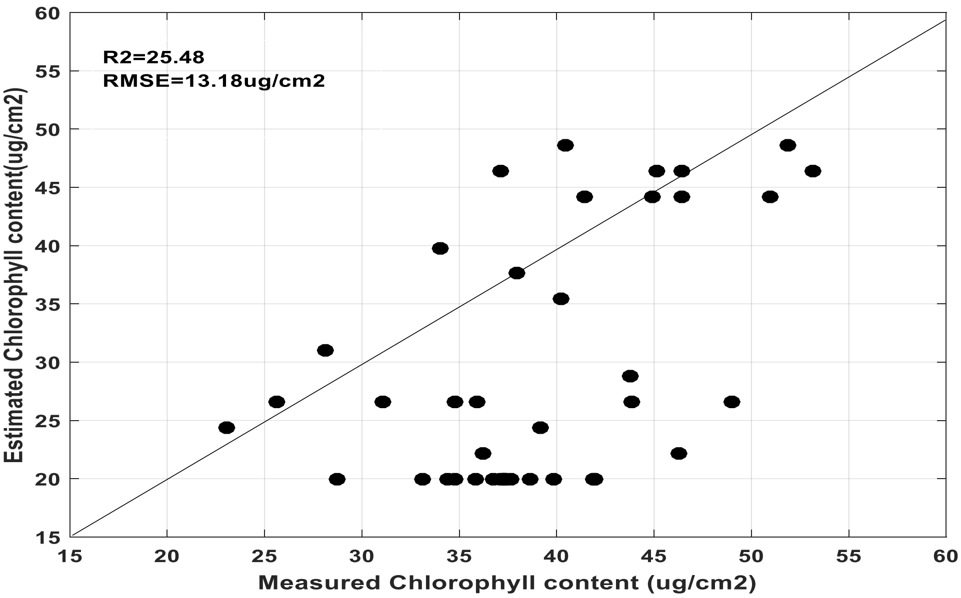


Figure 8: The relationships between the measured and retrieved leaf chlorophyll content using a systematically LUT generated by INFORM.

4.3.2. Chlorophyll retrieval using randomly generated LUT

The scatter plot in Figure 9 illustrate the relationship between the measured and estimated leaf chlorophyll content retrieved using the randomly generated LUT by INFORM. A relatively higher accuracy for leaf chlorophyll content was obtained when applying this method as compared to the result obtained using the systematic LUT in the previous section. The overall model accuracy obtained in this approach had root mean square errors of (RMSE=8.07ug/cm^2) and coefficient of determination (R^2=34.53%). It was also observed that this approach has resulted in lower relative root mean square of errors (rel.RMSE=20.69%) and bias value of 0.979. The higher accuracy obtained in this approach can be explained probably by the equal chance which exist for sample selection during LUT generation procedure. Similarly, the range of leaf chlorophyll content retrieved through this approach was found to be higher (i.e. 20.25-53.1ug/cm^2) which was closer to the range of actual measurements. A uniform distribution of points along the 1:1 line was observed from the scatter plot. The estimated leaf chlorophyll content has reached both the lower and upper boundary.

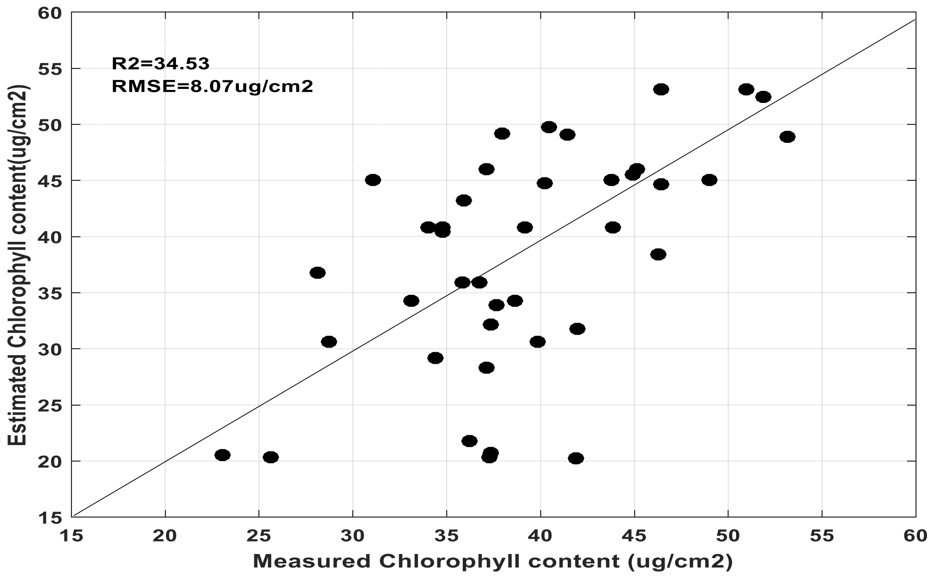


Figure 9 The relationship between the measured and estimated leaf chlorophyll content using the randomly generated LUT by INFORM.

4.4. The effect of red edge band on leaf chlorophyll retrieval

To investigate the importance of red edge band on leaf chlorophyll retrieval, the forward simulation of INFORM model was done without the inclusion of red edge spectral band and a new LUT was generated using the random approach. As stated in the previous section the randomly generated LUT has yielded higher prediction accuracy for leaf chlorophyll content. Figure 10 demonstrate the relationship between the measured and estimated leaf chlorophyll content using LUT generated without the red edge band. The root mean square error (RMSE) and coefficient of determination (R^2) were found to be 13.16ug/cm^2 and 25.13 %, respectively. It was also realized that removing the red edge band resulted in an increased relative root mean square of error (rel.RMSE=33.79) and bias value of 11.49. The scatterplot in figure 10 below shows the samples distribution in 1:1 line, in which most of the samples were located in the downside of the one to one line, indicating largely underestimation of the estimated leaf chlorophyll and occurrence of ill-posed problem. The range of the estimated leaf chlorophyll was between 20.21–41.17ug/cm^2. Compared with the results obtained in the previous section, using all bands for LUT generation, the upper range of the estimated leaf chlorophyll was dropped sharply. This has indicated the importance of the red edge band in leaf chlorophyll estimation.

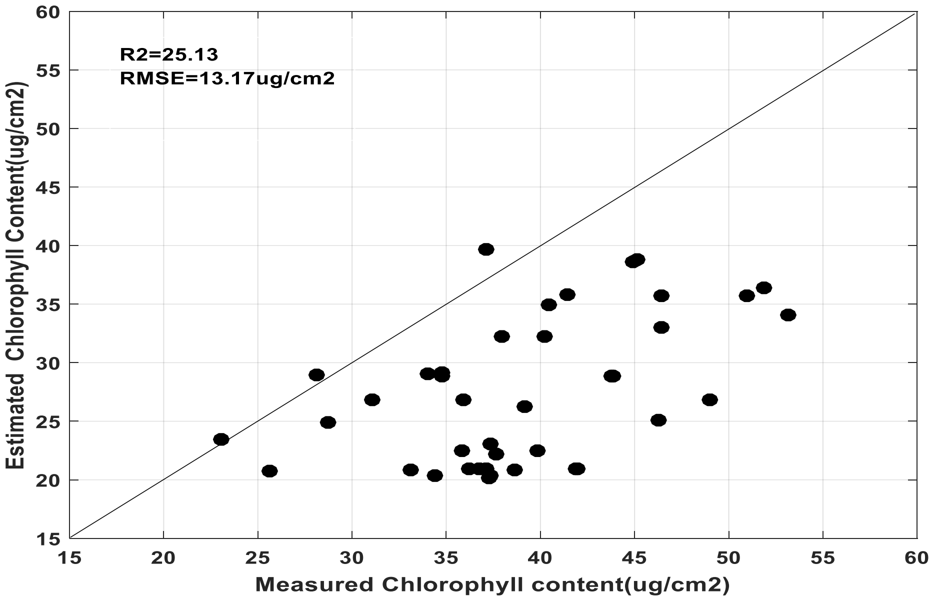


Figure 10 The relationship between the measured and estimated leaf chlorophyll content, using the randomly generated LUT without the red edge band.

4.5. Calculation of mean absolute error (MAE)

The mean absolute error (MAE) for individual bands were calculated between the measured and simulated reflectance obtained from the LUT inversion. The equation in (Atzberger et al.,2013) was used for calculating the MAE is shown below;

$$\text{MAE}(\lambda) = \frac{1}{n} \left| \sum_{k=1}^{n} Rmeasured(\lambda) - R\ best\ fit(\lambda) \right| \text{-------------------(Eq.11)}$$

Figure11 depict the MAE value calculated for each band. The result shows that among the five spectral bands, the blue band has a MAE of greater than 0.04, whereas the remaining four bands have MAE less than 0.02. This large difference demonstrates the presence of higher noise level in the blue band which is attributed to the atmospheric effect. Therefore, in the subsequent LUT generation, by removing this band its effects on leaf chlorophyll retrieval accuracy was examined. Similarly, here a random generation for LUT was considered.

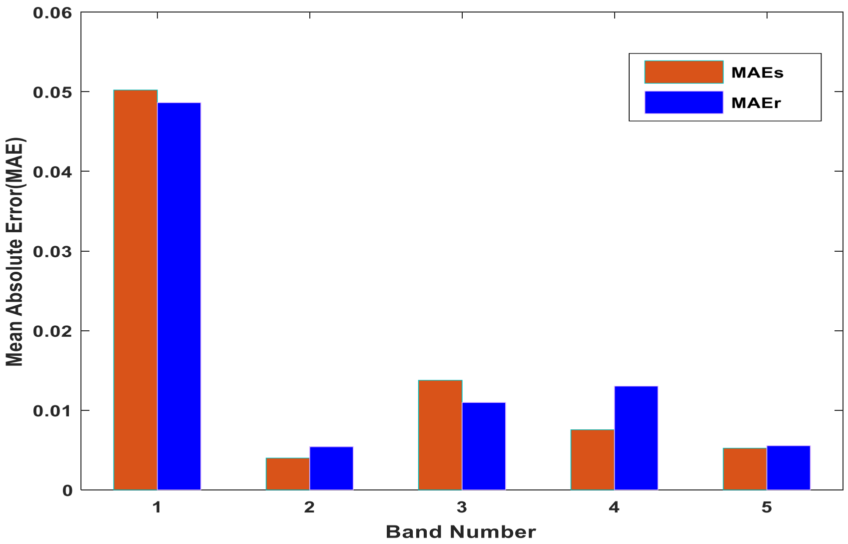


Figure 11: The mean absolute error (MAE) calculated from the best simulated reflectance and the RapiEye measured reflectance.

In the histogram, the red colour represents the MAE calculated from the systematic LUT inversion and the blue colour represents the MAE calculated from the randomly generated LUT inversion.

4.5.1. Chlorophyll estimation without the noisy band

The scatter plot (Figure12) shows the distribution of samples along the one to one line for the measured and estimated leaf chlorophyll content after removing the blue band from the model. Most of the sample points are relatively well distributed along this line. The range of estimated leaf chlorophyll content was found between 26 to 50ug/cm². This shows that the selected bands combination could relatively well predict the chlorophyll. The model has a root mean square error (RMSE) of 6.66ug/cm² and coefficient of determination (R^2) value of 36.74%. The relative root mean square error and the bias estimated were 17.07% and 2.85, respectively.

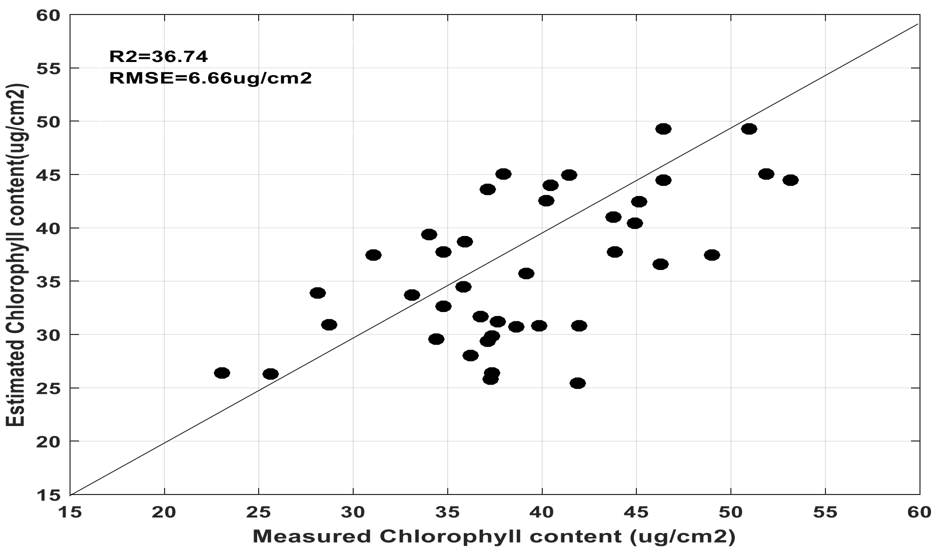
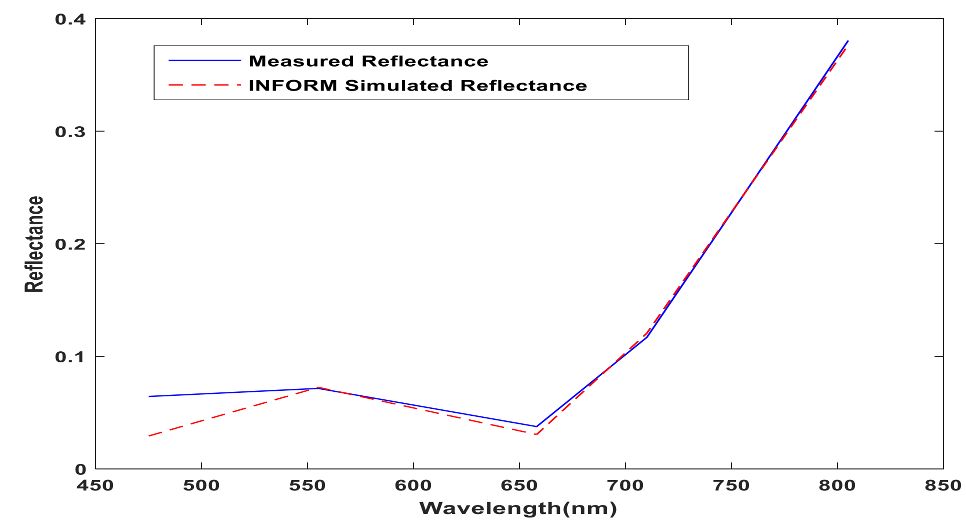
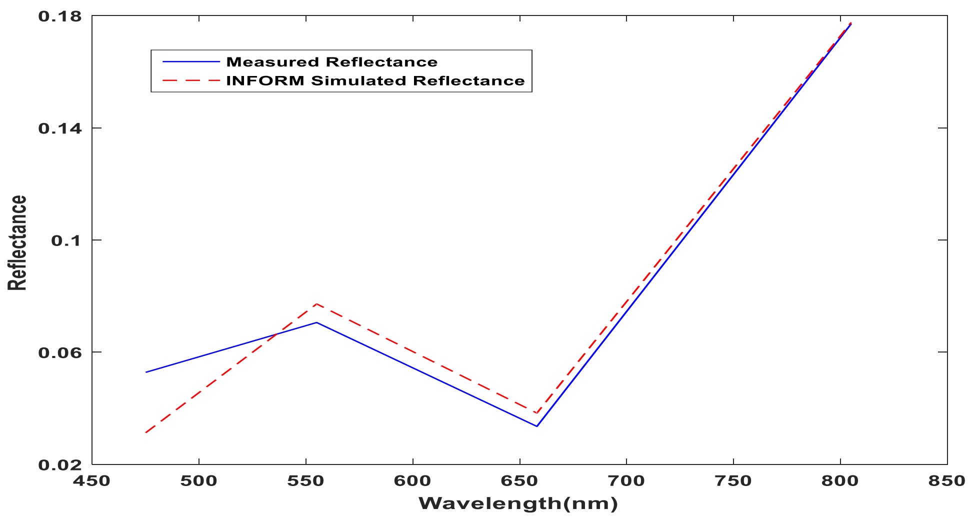


Figure 12 The relationship between the measured and estimated leaf chlorophyll after exclusion of the blue band from the modeling..

4.6. Model validation based on spectral match

The best matched spectra, from the INFORM simulated LUTs, with the RapidEye measured spectra are plotted in figure 13. In the inversion, the best matched spectra were selected based on their minimum RMSE values with the measured reflectance. The plot in top of figure 13 shows that when all wavelengths were utilized in LUT generation and inversion procedure, there is a spectral miss-match for the wavelength range between 475 – 550nm. This might be due to the effect of atmosphere impact on the blue band. Moreover, when the red edge band was excluded in the LUT generation and inversion, the miss-match were extended to other wavelengths, particularly those in visible region (middle plot in Figure13). In this case, the spectral miss matching was realized for the blue, green and partially in the red region (i.e. 475-660nm). However, when the blue band was excluded from the modelling, the simulated and measured reflectance was matched closely (last plot in Figure13). It seems that for the wavelength region after550nm, there exist better spectral match between the measured and simulated spectra. This result also confirmed the existence of noise problem associated with the blue band as it was also calculated from the MAE.





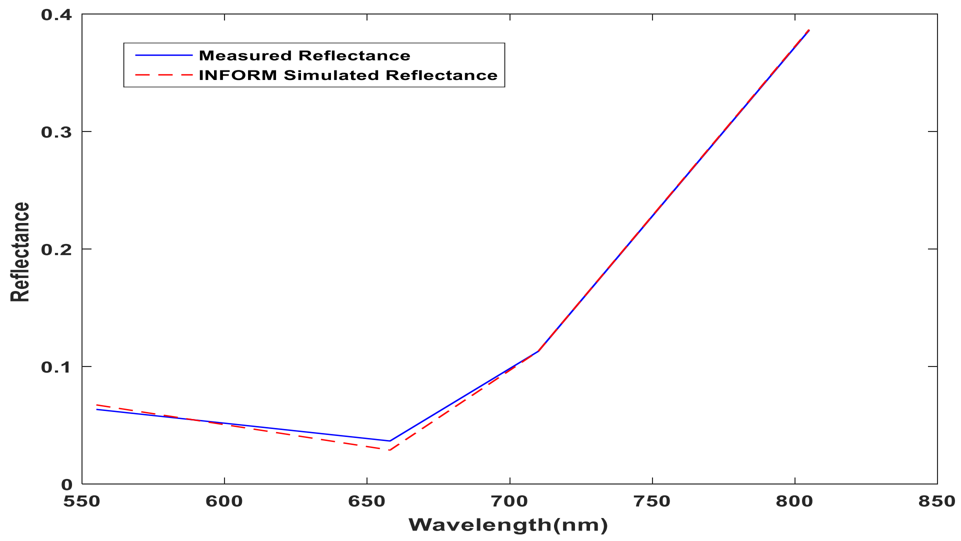


Figure 13: Comparison between the measured and best matched simulated spectra from the randomly generated LUTs: top (using all bands), middle (red edge band excluded) and Bottom (blue band excluded).

4.6.1. Plot wise root mean square error

Table 7 shows the corresponding root means square error between the measured and simulated spectra of the entire plot considered in this study (N=40). Larger descripancy between the measured and simulated spectra was seen when the simulation was done without red edge band. On the other hand, small variation was observed when the blue band was removed. Simulation done with all band had shown intermediate RMSE value. The detail of the plot specific RMSE value for each case was shown in Table 7 below.

Table 7: The Plot wise root mean square error between the measured and simulated reflectance

	Root mean square error(RMSE) in%		
Plot No.	Random LUT	Without Red edge band	Without Blue band
1	1.489	1.799	1.438
2	1.249	1.668	1.108
3	2.215	2.186	1.069
4	2.302	2.271	1.187
5	1.189	1.556	0.923
6	1.382	1.697	0.888
7	1.600	1.650	0.707
8	2.191	2.273	1.422
9	1.308	1.564	0.886
10	1.393	1.652	0.944
11	1.324	1.715	1.082
12	1.235	1.671	1.068
13	1.331	1.724	0.971
14	1.471	1.620	0.829
15	1.292	1.693	1.064
16	1.240	1.681	0.988
17	1.386	1.665	0.960
18	1.545	1.613	0.808
19	1.404	1.660	1.061
20	1.152	1.640	1.093
21	1.364	1.712	0.999
22	1.317	1.721	1.015
23	1.252	1.629	1.007
24	1.253	1.584	0.918
25	1.281	1.594	0.936
26	1.281	1.594	0.936
27	1.193	1.560	1.028
28	1.222	1.623	0.966
29	1.194	1.650	1.006
30	1.228	1.530	0.929
31	1.313	1.481	0.878
32	1.313	1.481	0.878
33	1.689	1.710	0.756
34	1.258	1.729	1.148
35	1.263	1.673	1.072
36	1.505	1.646	0.876
37	1.850	1.914	1.105
38	1.607	1.723	0.904
39	1.713	1.602	0.430
40	1.752	1.621	0.412

5. DISCUSSION

5.1. Overview

Foliar chlorophyll content is one of the most important biochemical component used as an indicator of plant photosynthetic activities and health condition. Measuring chlorophyll content from remote sensing data can be challenging because chlorophyll has a strong relationship with other leaf foliar biochemical elements (Barry & Newnham, 2012). Therefore, in order to quantify this unique and complicated leaf trait, there is a need to select proper model that is capable and robust. Besides, the complicated nature of the variables being studied (leaf chlorophyll content), the level at which the estimation was done (using image reflectance) also constrained by several factors. Stand structures, species types, and background reflectance are among the main factors hampering canopy reflectance obtained from imagery. Therefore, considering all the mentioned factors, INFORM canopy radiative transfer model and Look Up Table (LUT) inversion was applied to simulate the forest reflectance and the result were evaluated against the RapidEye measured reflectance based on the criteria of RMSE and R^2.. The results obtained from this were discussed in the subsequent subsection.

5.2. The effect of input parameters on simulated reflectance

The result from INFORM model sensitivity analysis has indicated the most important vegetation parameters influencing forest canopy reflectance in selected (RapidEye) wavelength region ranging between 475 – 805nm. It was observed that most of the canopy stand parameters have great variability in these wavelength regions. This result agrees with earlier studies by Yuan et al.(2015) ;Ali et al. (2015) and Ollinger(2011) who demonstrated that at canopy level, stand parameters are mainly effecting the reflectance.
Further studies by, Verrelst et al. (2008) and Verrelst et al. (2010) investigated factors such as the woody elements as the main constraint factors affecting canopy spectra under heterogeneous forest condition. According to their finding this effect would be higher when the crown cover is less than 30%. This condition also applies to the case of Bavarian Forest National Park ecosystem, as there are many dead stand wood elements mixed with living trees, thereby influencing the reflectance measured by the sensor.

The effect of leaf chlorophyll on canopy reflectance was mainly observed in the wavelength region between 440 to 750nm in this study (RapidEye spectral region) (Figure 7). The chlorophyll absorption bands sensitive to chlorophyll pigment levels are mainly situated in the visible to the shoulder of near infrared region (Gitelson & Merzlyak, 1997;1998). Particularly the green and far red region high sensitivity to reflectance are linked to chlorophyll content (Datt, 1998). Further from sensitivity analysis of the simulated data, it was observed that the impact of dry matter content was minor for the visible region but its effect was significantly increased beyond 750 wavelengths toward the mid-infrared region. Earlier studies confirmed that water content and dry matter content have an impact on reflectance for the region beyond near infrared and only minor effect associated with dry matter had been observed in the shoulder of near infrared region(Ollinger, 2011).

5.3. Effect of LUT approaches on chlorophyll content

The effect of different look-up table generation methods on chlorophyll estimation was evaluated using the INFORM radiative transfer model. The study was performed by simulating two independent LUTs. The canopy reflectance data sets for the two LUTs in this study were randomly and systematically generated. It was found that the inversion performed using the randomly generated LUT has yielded relatively better prediction accuracy for chlorophyll retrieval (RMSE=8.07ug/cm2 and R^2=34.53%) as compared to using the systematic generated LUT. The result obtained in this study was in agreement with that of Maire et al. (2008) who used the PROSAIL model and hyperspectral indices for estimating leaf chlorophyll and obtained RMSE of 8.2ug/cm^2 which is comparable to the result obtained in this study. The higher prediction accuracy obtained in the case of randomly generated LUT can be linked to the nature of sample selection while generating the LUT. The random nature of sample selection means that all the samples or the parameters have equal chance/probability of selection during the simulation of spectra; hence, better representation can be achieved. Consequently, this has impacted the model prediction accuracy obtained by applying this inversion approach. This is in agreement with the earlier study by Weiss et al.(2000) who suggested the importance of employing proper sampling of canopy variables included during the LUT generation in order to optimize the model efficiency hence better realization of actual ecosystem condition.

The achievement of lower model accuracy in the case of utilizing systematic LUT might be explained by the reason that this method requires manually setting the ranges/steps of input parameters varying during the model parameterisation. However, the manual input parameter setting during the LUT parameterization is exposed to operator/programmer error and consequently, this affects the model performance(Dorigo et al., 2007). It was also observed from figure10 that less representation of data was obtained from the model. The ill-posed nature of the physical model as it was stated in Combal et al., (2003) was clearly observed for the systematic LUT generation approach employed in this study.

It was noted that the accuracy of chlorophyll retrieved in this study was lower when compared to other studies for different ecosystem condition such as Zarco-Tejada et al.(2001) who estimated chlorophyll in the closed forest canopy (RMSE= 3-5.5ug/cm^2). Similarly, Moorthy et al. (2008) estimated chlorophyll content for conifers forest with RMSE values equal to 5.3ug/cm^2. Likewise, this result also lower than Croft et al., (2013) who evaluated different satellite for forest leaf chlorophyll estimation. Furthermore, the accuracy of leaf chlorophyll estimated in this study was also found to be lower when compared with chlorophyll estimated using multispectral data and different canopy models for other ecosystem such as for rice (Darvishzadeh et al., 2012) and grassland (Yin et al, 2016). The poor relationship captured between the measured and estimated leaf chlorophyll for this study could be due to the presence of poor signal propagation from the leaf to canopy level affecting the reflectance detected by the sensor (Jacquemoud et al., 1996). However, the accuracy obtained in this study is higher than those obtained by Yang,et al.(2010) who used PROSPECT and SAIL canopy models for forest chlorophyll estimation using Hyperion data and look up table inversion. Likewise, our result also outcast the result obtained by Malenovský et al.(2006) who estimated leaf chlorophyll in forest using 3D Discrete Anisotropic Radioactive Transfer (DART) model and hyperspectral data.

5.4. Effect of inclusion and removing red edge band on chlorophyll estimation

The potential of red edge band was investigated for leaf chlorophyll estimation. The INFORM model was calibrated with and without red edge band and were used to generate both random and systematic LUTs. It was observed that a relatively higher retrieval accuracy for leaf chlorophyll was achieved when the red edge band was included in the INFORM model. A similar result was obtained by Delegido et al.(2011) who evaluated the red edge band available in Sentinel-2 for chlorophyll estimation. In their study, they found that the exclusion of red edge band from inversion canopy chlorophyll estimation had resulted in poor model prediction accuracy. Similarly, the inclusion of red edge band had greatly improved the retrieval of canopy chlorophyll content. In our study the relative contribution of red edge band inclusion in the LUT inversion resulted in an increment of 9.4% R^2 and lowered the RMSE by 5.1ug/cm2.

5.5. The effect of LUT approaches on reflectance

The comparisons of the reflectance spectra simulated by INFORM using random and systematic approach against the RapidEye reflectance had shown a relatively better matching between the measured and simulated spectra, when the simulation was performed using randomly generated LUT (R^2=98.4%). Spectral mismatch was seen for the wavelength region between 475-550 nm (Figure 13 top). On the other hand, the reflectance simulated without the inclusion of red edge band had shown a larger discrepancy from the actual reflectance measured by the sensor(R^2 =96.36%). This reveals the importance of red edge band in characterising the vegetation reflectance (Delegido et al., 2011; Schuster et al., 2012). Furthermore, this could be explained by the inefficiency of the bands included in the modelling (i.e. due to the atmospheric noise). Particularly this mismatching was seen for the wavelength 475-700nm this represent blue-red band region. Furthermore, when the LUT were generated by excluding this region (blue band), the simulated reflectance had shown a higher match (R^2=99.94%). The spectral matching between the measured and simulated reflectance after removing the blue band has proved the presence of noise in this band. This result indicates the necessity of atmospheric correction as well as band selection during LUT inversion. The correlation between the measured and simulated reflectance for the systematically generated look-up table was lower and a great mismatching was observed (not shown).

5.6. The source of error and the way to improve

Evaluating the overall performance of the INFORM canopy radiative model demonstrated that an $R^2$of less than 0.5% and an RMSE=8.07ug/cm2 were obtained when leaf chlorophyll retrieval was examined. The reasons are summarized as following.

As mentioned earlier, the low R^2 and high RMSE value obtained in this study can be justified due to the existence of poor signal propagation from the leaf to the canopy level leading to poor estimation of leaf chlorophyll content (Darvishzadeh et al., 2008; Jacquemoud et al., 1996). Furthermore, Weiss et al. (2000) suggested the reflectance in heterogeneous forest could have been be widely affected by the intrinsic nature of the forest. This also applies to our study area where the vegetation is characterized with heterogeneous. This tendency could be more aggravated if the selected sensor types have a higher spatial resolution capable of capturing the detail heterogeneity of the ecosystem which intern affects the canopy reflectance(Barton, 2001; Wang & Li, 2013; Weiss et al., 2000; Zarco-Tejada et al., 2013). Fourty & Baret.(1997)evaluated the efficiency of different spatial resolution (i.e. 10 and 20 m) for estimating canopy biochemical and biophysical elements and found that the lower spatial resolution yielded better-estimated result than the higher resolution sensor. A further justification could be due to less smoothening nature of existing noise that possibly be captured by the sensor originating from the surface heterogeneity(Zarco-Tejada et al., 2013).

The ill-posed nature of the model inversion that was mainly observed during systematic LUT generation, could also lead to poor model performance (Combal et al., 2003). Likewise, the lower accuracy achieved in systematic LUT was linked to the level of precision made during the initial setting of model parameterization.

The chosen models, in this case, INFORM could also be the case for obtaining low leaf chlorophyll retrieval accuracy. In INFORM the forest is represented as a full green area without any open space, as described in Atzberger(2000) and Schlerf & Atzberger(2006) therefore, the model simulate canopy reflectance by assuming this condition which by itself is liable to biases.
This assumption might be pronounced if the vegetation being investigated is sparser/ less dense resulting in an increase in background reflectance(Garcia-Haro & Gilabert, 1999; Wang & Li, 2013). In this study, lower stand density was obtained with an average tree density of 307 per hectare which is lower than density reported for the site by (Ali et al., 2015). The lower density implies the presence of open space with higher effect of surface background thereby affects the reflectance captured by the sensor.

Although the importance of performing atmospheric correction for retrieval of chlorophyll was suggested by (Dong et al.,2009), in our study the atmospheric corrections were neglected due to technical problems. However, the effects of the atmosphere were observed from the calculated mean absolute error for bands. Particularly this artefact was highly reflected in the blue band. Consequently, including the information acquired through this band during the inversion has resulted in lowering the model performance. The model accuracy was improved when this band was removed from the inversion. Meaning the acquired image has constraint by the atmospheric impact.

In this study we have investigated the best band combinations from RapidEye image for estimating chlorophyll content. Consequently the best band combination was when the blue band was removed and red edges, red and green were included in the inversion. When the INFORM model inverted using these band combination the overall model accuracy was improved as compared to the whole bands base retrieval. The importance of choosing optimal band combination was suggested earlier by Weiss et al.(2000), hence, the selection of appropriate band needs care and has to be done systematically.

6. CONCLUSION AND RECOMMENDATIONS

In this study, we evaluated the applicability of broadband multispectral satellite imagery and INFORM radiative transfer model for modelling leaf chlorophyll content in Bavarian Forest national Park. For successful retrieval of chlorophyll content, the study employed two looks up table (LUT) inversion approaches namely random and systematic generated. Furthermore, in this study the importance of red edge band for chlorophyll estimation was also evaluated. The overall result obtained in this study had shown the moderate suitability of INFORM model for simulating canopy reflectance for this selected study area. The model best overall accuracy obtained was RMSE =8.07ug/cm^2 and R^2= 34.53%. The randomly generated look up table approach outperformed the systematic lookup table for retrieving leaf chlorophyll content. Furthermore, the exclusion of the red edge channel from the inversion had resulted in poor model prediction accuracy and this has indicated how red edge channel embedded in the RapidEye image is important for chlorophyll estimation. Removing the noisy band from the inversion increased the model accuracy and created a good spectral match between the modelled and measured spectra. The results indicated the potential of INFORM and RapidEye satellite sensor for estimating chlorophyll, particularly when modulated chlorophyll (chlorophyll*LAI) at the canopy level would be considered.

6.1. Summary for answering the proposed research questions

- **Research question**: Does the LUT generation approach affect the retrieval accuracy of leaf chlorophyll content? Which approach of LUT generation, for inversion of INFORM will provide a more accurate estimate of leaf chlorophyll content?

- **Answer:** Yes**.** The two LUT approaches employed for this study had shown a significant difference in their chlorophyll retrieval accuracy. Using the randomly generated look up table approach a higher chlorophyll retrieval accuracy was achieved (R^2=34.53, RMSE=8.07ug/cm2, and relative RMSE=20.69%, Bias= 0.979)

- **Research question:** What are the advantages and disadvantages of utilizing high-resolution multispectral imagery (in particular RapidEye) for estimating leaf chlorophyll content?

- **Answer:** Based on the result in section (4.3.2) where chlorophyll retrieval was examined with the inclusion of red edge band, higher chlorophyll retrieval accuracy (RMSE=8.07ug/cm^2) was obtained. The exclusion of red edge channel from inversion had resulted in lower model retrieval accuracy of (RMSE=13.17ug/cm^2). This has clearly indicated the importance of red edge band included in RapidEye image for chlorophyll retrieval hence considered as one advantage. On the other hand, when using broadband multispectral satellite imagery like RapidEye there could be over generalization of information that result in lower chlorophyll retrieval accuracy which is also the case in this study.

- **Research question**: Which band combinations give higher chlorophyll retrieval accuracy in terms of RMSE and R^2?

- **Answer:** Higher leaf chlorophyll retrieval accuracy was attained using four bands combination (i.e. band2, band3, band4, and band5) excluding the blue band from the inversion (RMSE=6.66ug/cm2 and R^2=36.74%).

6.2. Further recommendation for the future studies

Generally, in this study, we evaluated two look-up table approaches for leaf chlorophyll retrieval under heterogeneous forest condition using INFORM canopy radiative model and high-resolution multispectral satellite image(RapidEye).Therefore, taking all the challenges and opportunities we recommend further research investigation on the following topics:

- Since the present study focused only on estimating chlorophyll at leaf level from canopy spectra, therefore, we recommend further research to consider retrieval of canopy chlorophyll content from image.

- It was suggested that woody component has a significant impact on forest canopy reflectance. Similarlly in our study area, part of the forest is covered by dead standing trees and also there are situations in which dead trees are found mixed with living trees hence affecting the reflectance captured by the sensors. Therefore, future research has to take into consideration the effect of these factors for modelling forest chlorophyll.

- In order to draw valid conclusion on the usability of RapidEye image and INFORM model for estimation chlorophyll content under heterogeneous forest ecosystem further modelling research has to be explored by stratifying the forest into single trees species base, based on age of leaf/ trees, and single band base.

- Other machine learning algorism likes SVM; MRF-VHR has to be evaluated beside the LUT and compare their efficacy for leaf chlorophyll retrieval.

- To evaluate the high spatial resolution attribute of the RapidEye satellite image for chlorophyll estimation under heterogeneous forest condition further comparative analysis research with data derived from other satellite (Landsat 8, Semtinel2) needs further exploration.

- The model assumptions on the parameters such as soil background reflectance and N structural parameters could be the main sources for lowering the model accuracy hence their relative effects on leaf chlorophyll retrieval needs further investigation through employing site specific information.

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