Chapter 2

Literature Review

2.1 Overview

The study is area-specific and imputes a specific methodology for problem definition. Forest health is the main problem of the study area due to increased mining activity which triggers subsequent problems for the surrounding ecosystem. In this chapter, the literature review has been done from two perspectives. The first perspective covers the general forest aspects, and secondly, from the remote sensing (multispectral and hyperspectral) based methods for forest health assessment and risk prediction. Objectives wise relevant literature review has been highlighted in this chapter.

2.2 Forrest health assessment

2.2.1 Forest health

Forest health defined by the production of forest conditions, which is directly dependent on nature and humans. The term 'forest health' is defined in many comprehensive literature reviews. The American forest society defined 'forest health condition' depends on forest age, composition function, structure, vigor disease, or presence of unusual levels of insects and resilience to disturbance (Ostry & Laflamme, 2008). From the ecosystem-centered perspective, forest health is defined as resilience, persistence, and biophysical processes, which lead to sustainable ecological conditions (Johnson et al., 2009). Biotic and abiotic disturbances have significant impacts on forest health and vitality of forests. It may result in substantial economic and environmental losses (Trumbore et al., 2015). Forest health class, healthy and unhealthy, depends on biotic, climate, human, and atmospheric or biogeochemical parameters (Wingfield et al., 2015). Chazdon (2008) defined forest health as follows: the term forest health should be restricted to the examination of the role of biotic and abiotic agents in ecosystem processes. Some literature defined forest health as Pastenes et al. (2003), "a healthy forest is an ecosystem in balance." The primary cause that affects forest health is the different types of climate variations like increasing temperature, drought, acid rain, air pollution, and deforestation, etc. (Dale et al., 2001; Woods et al., 2010). Forest health depends on various factors, such as the concentration of water and chlorophyll, leaf pigment, carbon component, and photosynthesis efficiency (Khare and Arbind Kumar, 2014). The effective forest health protection requires the different types of evidence to round the forest condition on rates of growth, stocking of levels, fuels, diversity, and age. Some invasive species are also the primary cause of forest health deterioration (Moore & Allard, 2008). Forest health monitoring is a new way to understand foliar chemistry. To better understand foliar chemistry, which is related to the canopy, the biochemical analysis is performed (Rothe et al., 2002). The forest health monitoring has a significant benefit since vigor infectivity is often connected to various proceedings, for example, climate change and phenology of forest species type and monitoring of forest health will provide an idea about the health of the forest resource (Stone and Coops, 2004; Bonan et al., 2008).

2.2.2 Application of remote sensing and GIS in forest health assessment

The studies are available for forest health assessment based on remote sensing. The false-color aerial photographs and multispectral sensor-based satellites image provide red edge related bands based vegetation indices (Normalized difference vegetation index (NDVI), Leaf area index (LAI) were applied for forest health monitoring (Allen et al., 2010). Ismail et al. (2007) studied forest health using high-resolution multispectral imagery and used NDVI, Difference vegetation index (DVI), Ratio Vegetation Index (RVI) and Green Normalized Difference Vegetation Index (GNDVI) indicators for the detection of the healthy and unhealthy forest. Detection of vegetation health and stress by remote sensing technique is based on the assumption that vegetation stress factors interfere with photosynthesis or the physical structure of the vegetation and affect the absorption of light energy and thus alter the reflectance spectrum of the plant (Lausch et al., 2016). Chlorophyll content of leaves is an indicator of forest health. NDVI obtained from multispectral remote sensing data is used as an indicator of chlorophyll content and the health condition of the forest (Wilkie et al., 2004). Some researchers have used remote sensing-based vegetation indices (Red Edge (RE)-NDVI, Carotenoid Reflectance Index (CRI1), and Water Band Index (WBI) for forest health assessment (Singh et al., 2014; Roy et al., 2002). In many studies, Landsat OLI and Ikonos sensor data are used for mapping of forest health conditions, and their accuracy was compared (Wang et al., 2015). Several studies had been done to monitor vegetation health using remote sensing-based water content bands. Water is essential for the survival of vegetation. Therefore data indicating water content is required to monitor vegetation health (Roy et al., 2002; Zhai et al., 2013).

The studies are available for forest health assessment based on hyperspectral remote sensing. Hyperspectral remote sensing is a very useful tool for forest health monitoring, and it offers high accuracy as compared to multispectral data. The hyperspectral remote sensing data acquisition from satellite-borne spectrometers have opened new areas of forest research that could bring revolutionary changes in the current approaches to forest health management (Franklin, 2001; Marshall et al.,2016). Hyperion, which senses 242 narrow spectral bands within the 400-2500 nm wavelength of the electromagnetic spectrum, detect forest strength and biological variations in forest health. (Varshney & Arora, 2004). The hyperspectral satellite image visible red band, the distinction in the reflectance is highest at near-infrared (NIR), and Red bands concerned vegetation indices (NDVI and LAI) were used for forest health mapping. (Jiang et al., 2008). Hyperspectral remote sensing plays a significant role in the process of physiological assessment of vegetation and analysis of leaf's spectra, for example, the relationship can be established between Red-NIR edge bands and chlorophyll content (Clevers, & Kooistra, 2012). Hyperspectral satellite image provides forest health-related data, such as LAI and partial wrap, in addition to the ratio of water, dry affairs, lignin, chlorophyll, and nitrogen (Soudani et al., 2006). ENVI's Forest health tool was used to classify forest health and defoliation pixels of forest (Tuominen et al., 2008). They have used narrow-band vegetation indices (VIs) as input in the forest health tool of ENVI. The support vector machine (SVM) and Spectral Angle Mapper (SAM) classification based on Hyperion data carried out for forest health mapping. It generates a spatial map that shows the general forest strength and vigor of a forested area. It can detect pest and blight conditions in a forest as well as assessing areas for timber harvesting (Tuominen et al., 2009; Pu. et al., 2003).

Many studies to monitor forest health, has been done using spectral laboratory and ground-based survey data. Meng et al. (2016) have developed a spectral signature library to express the quality parameters of standing vegetation. This signature has provided the quality of vegetation health relating to the presence of plant biochemical processes, water content, etc. The vegetation spectral laboratory was used to classify the healthy and unhealthy pixels of Hyperion image for significant information acquisition for forest management purposes (Gong et al., 2003). Tree spectral signatures and Hyperion data used forest health assessment in Yelagiri Hills, Tamil

Nadu (Kumaresan, 2018). They had used the classifications (SAM) method and field-collected tree spectra as input for forest health class classification. Meng et al. (2016) studied forest health based on textural and spectral information extract from SPOT 5 satellite imagery and field-based spectroradiometer. They ran a statistical model to get FHI (forest health index) map for the Guangxi region.

2.3 Identification of local tree species and plant diversity estimation

2.3.1 Tree species classification and plant diversity estimating

The tree species and its diversity are the most important natural resources that are related to the forest, environment, and human. Mining related activities have shown a high potential to goad forest growth and species health problem (Dale et al., 2001). The mining activities cause forest degradation, damage, and deterioration of biodiversity, as well as ecological and medicinal plant damage (Raizada & Samra, 2000). Gibbs et al. (2016) have studied deforestation of the Amazon forest area. They have shown that 9 % of forest was lost by mining activities between the years 2005 to 2015. The tree is the major structural and functional basis of the forest ecosystems (Sahu et al., 2012; Naidu & Kumar, 2015; Seth, 2003). The tree diversity has several ecological functions. Disturbances directly affect the diversity, distribution, and abundance of tree species, e.g., the effect of animals in forest protected areas (Bruce et al., 2008), land-use conversion (Fuller, 2006), and harvesting for fuelwood (Madubansi & Shackleton, 2006). The iron ore belt of the Saranda forest started facing trees species degradation due to mining activities for the last 25years (FSI report). This resulted in the change in natural tree patterns and species biodiversity over the years.

2.3.2 Remote sensing and GIS application in tree species classification

This study focusses on tree species classification using satellite imagery and field spectra. The advances of hyperspectral remote sensing technology show the potential of monitoring the dynamics of the forest at spatial and regional scale level (Chambers et al., 2007; Plaza et al., 2009). In remote sensing (and so as in Hyperspectral), the reflected wave (electromagnetic) is captured, and it lies in very narrow bands. The bandwidth of narrow bands lies between 0.3 to 2.5um. There exhibits variation in the captured reflected waves due to different textures of tree species at its different growth stages. Consequently, the satellite observes differences in the received signals from various trees (Thenkabail & Lyon, 2016; Borengasser & Watkins, 2007). Hyperspectral Compact Airborne Image (CASI) sensor data had used for tree crowns and species classification (Bunting & Lucas, 2006). They had developed the algorithm to delineate tree crown and species using ECognition expert, and ground spectra data based on spectroradiometer. One airborne (HyMap) and one spec-borne (Hyperion) hyperspectral satellite imagery (pixel resolution size of 8 and 30 meters) had been used for tree species classification (Ghiyamat et al., 2013). They had used SMTs (Spectral measure techniques) method and ground spectra data for the classification of tree species. The hyperspectral remote sensing technology has provided high accuracy to discriminate tree species by classifying it at spatial scale level .The Multispectral (0.5m) and Hyperspectral (4nm) resolution satellite imagery was used for tamarisk tree species classification. The best method for Tamarisk tree classification is identified by comparing the multispectral and hyperspectral data (Dalponte et al., 2013). They had used the Efficient hierarchical clustering statistical (EHCS) method for identifying the tree species with suitable wavebands. The Hyperspectral remote sensing and Lidar data were used for forest species classification and tree height measurement. Some researchers had developed the Individual Tree Crown (ITC) method for the classification of tree species (Anderson et al., 2008; Alonzo et al., 2014; Dalponte et al., 2014). They had used various thresholding methods for full pixel tree species classification and compared them with the ITC method. Space-borne and airborne data were applied for species diversity, biomass mapping, species classification, and tree height measurement in various forest areas (Van et al., 2007; Koch, 2010; Cho et al., 2010). They had used hyperspectral and Lidar data, and multiple-end member SAM approach for tree canopy level analysis and classification. Some researchers had used Beiman cutler classification (BCC) in the R statistical program package using the RF algorithm for tree species classification (Kozoderov et al., 2015a; 2015b). Location-based individual tree species classification is a new task. Three algorithms (Adaboost, Tree ensemble, and random forest) were used for tree species classification (Chan & Paelinckx (2008); Laurin et al., 2014). They had used airborne hyperspectral data, and field spectra data for species classification. Based on spectral behavior, the tree species classification is carried out. The spectral response of tree species depends on leaves reflectance, absorption, and transmission properties. A spectral collection technique (SCT) is one of the significant element in the discrimination analysis of tree species (Adam et al., 2010; Delalieux et al., 2009). Indian tropical forest tree species (Mango, Madhuca, Ficus, bamboo, Pongamia, and mixed-vegetation) were classified using ANN, SAM, and SVM based algorithms (Vyas et al., 2011a, 2014b). They had used the PLS error model for bamboo, teak, and mixed spectra analysis.

2.3.3 Remote sensing and GIS application in tree species diversity estimating

In the 1960s, the terms species diversity was first introduced (alpha, gamma, and beta biodiversity) and measured at different spatial regional scales. Alpha biodiversity denotes forest-specific species diversity. It expresses the total number of tree species or species richness. The species diversity indices, such as Shannon's diversity index (H), Simpson index (D), which are widely used, also indicate the abundance of species (Rocchini et al., 2010; Gorelick, 2006). For a better assessment of tree species diversity, mapping at regional scale level based on hyperspectral narrow banded indices and ground spectra data was done (Peng et al., 2018). They had used 1st order derivation value for each wavelength, and 37 narrow banded indices were used for species diversity mapping. Assessment of species biodiversity has been carried out using satellite imagery data (Nagendra & Gopal., 2011). For example, Lidar and Radar-based remote sensing data have been used to evaluate the relationship between species diversity, (Simonson et al., 2012) animal richness and 3D structure. The near-infrared (NIR), middle infrared (MNIR), and Thermal Infrared (TIR) have strongly detected the species diversity. The NDVI indices were used to estimate the Shannon and Simpson species indices (Kiran & Mudaliar, 2012). The airborne hyperspectral and thermal-Infrared satellite imagery were applied for the detection of species diversity and vegetation (Dudley et al., 2015; Coates et al., 2015). Hyperspectral images (airborne and spaceborne) showed the highest accuracy results of species biodiversity in different forest area, including rain (Ghazoul & Sheil 2010), tropical (Nagendra & Rocchini, 2008) and mixed (Schneider et al., 2017), conifer (Nagendra, 2001) and deciduous forest (Decocq et al., 2004). The tree species richness or biodiversity in forest areas are positively affected by the multiple ecosystem functions (Griffin et al., 2009). The statistical methods (hierarchical cluster, standard deviation, and linear regression) have been used to estimate plant diversity, as well as 1st and 2nd order derivatives of spectral values were used for estimation and justification of species diversity (Laurin et al., 2014; Tuanmu; Jetz, 2015). The multispectral

Unmanned Aerial Vehicle (UAV) (Getzin et al., 2012), airborne (Lassau & Hochuli, 2005), and spaceborne (Nagendra & Rocchini, 2008) data were used to, and it has provided very high accuracy results in the assessment of forest biodiversity. Some researchers have shown the relationship between spectral indices and plant diversity. They have used the hyperspectral narrow banded indices, field spectra, and forest survey data for analysis of species diversity as well as shown high accuracy mapping of species diversity. The species diversity mapping was done by hyperspectral narrow banded indices with an error of 20 % in grasslands forest of Sweden, as well as a temperate forest of Germany (Möckel et al., 2016; Leutner et al., 2012). The combination of hyperspectral and multispectral (world view) imagery was used for species diversity and tree species mapping. The accuracy yielded by multispectral (77.5) data has also been compared with hyperspectral (79.2) data (Cho et al., 2012). Species diversity and tree species maps will help in forest management, as well as in decision making for plant landscapes.

2.4 Foliar dust estimation and mapping

2.4.1 Foliar dust

Some studies were available for foliar dust estimation, vegetation, and environmental effect based on different methods. Dust can physically affect the photosynthetic and transpiration rate of leaves in some ways operating singly or in combination (Ernst et al., 1982). Dust particles may block leaf stomata, tissue, (Ricks and Williams, 1974; Kulshrestha et al., 1998), and dust effects are also highly dependent upon leaf age deposition time. Whatever combination of dust effects occurs, the net result of extensive dust loading is reduced plant growth (Sharifi et al., 1997). Some recherché scholars have analyzed the dust deposited on the leaves. They have used scanning electron microscopy (SEM) to investigate the morphological structure and dust trapping capacity of the sample leaves (Simon et al., 2014). They have found that the leaves surface with a high density of trichomes helps in decreasing the level of dust or air pollution. Liu et al., (2017) have determined plant species which can accumulate air dust and associated heavy metals. They have used Metal Accumulation Index (MAI) for multi-metal pollution measurement. They have suggested that these determined plant species can be planted at large traffic roadside of urban areas to reduce the amount of dust. One researcher has determined the influence of human activities in the emission and deposition of dust in the atmosphere (Neff et al., 2008). Borka (1984) has discussed the effect of metalliferous dust from dressing works on the growth, development of crops, and plants. Paling et al. (2001) have examined the impact of iron ore dust on the stomatal damage of mangroves. They have found that the iron ore dust has affected mangrove's health by some other mechanism like increasing temperature, shading, or a restriction of transpiration by the thickness of the dust on the abaxial surface.

2.4.2 Remote sensing and GIS application in foliar dust estimation and mapping

Some studies were available for foliar dust estimation based on remote sensing data. Ma et al. (2017) have tested eight different vegetation indices (VIs) to estimate foliar dust in the ultra-low-grade magnetite mining area. Only multispectral based NDVI was useful, and the other seven vegetation indices (Simple Ratio (SR), Soil Adjusted Vegetation Index (SAVI), and Transformed Soil Adjusted Vegetation Index (TSAVI), Perpendicular Vegetation Index (PVI), Non-Linear Index (NLI), Modified Soil Ratio (MSR), and Tasseled cap (TC) greenness) were not helpful because the study area selected for this research work is not much suitable to use those indices. Tuominen et al., (2008) have determined the Environment for Visualizing Images (ENVI) software forest health tool is useful for detecting dust and seepage contaminated forest and mining areas from the multispectral satellite image. Kamruzzaman et al. (2015) have determined a model for estimating dust on leaves with the help of multispectral remote sensing data. They found the near-infrared region is the more relevant band to detect dust on leaves. Stone & Coops (2004) have developed a method for monitoring forest health as well as foliar dust with the help of Lidar and multispectral satellite data. They have shown the high- resolution Lidar, and multispectral data appears to be a suitable tool for foliar mass or defoliation measurements.

Few numbers of the international studies were available for foliar dust estimation based on hyperspectral satellite imagery and field measurement dust data. Zhu et al., (2017) have developed a method for presymptomatic detection of leaves infected by tobacco disease with the help of hyperspectral imaging technique and machine learning models. They have used the successive projection algorithm to reduce the number of wavelengths and machine learning models used to identify and classify the stages of tobacco disease in plants. Merzlyak et al. (2003) have determined three spectral bands to estimate total carotenoid's dust content in plant leaves. They have developed and used an index for evaluating dust carotenoids in plant leaves. Tuominen et al. (2009) have determined vegetation indices (VIs) to detect dust contaminated forest areas. They have found NDVI, Anthocyanin Reflectance Index (ARI_700), and Photochemical Reflectance Index(PRI) vegetation indices were useful in identifying dust contaminated forest and mining areas. Zhang and Reid (2010) have developed a method to detect dust and smoke over land and water. They have used Aqua and Terra MODIS (Moderate Resolution Imaging Spectroradiometer) data for detecting dust and smoke on land and water. They have evaluated the smoke and dust detection with the help of MODIS Aerosol Optical Thickness (AOT) images. They suggested that the method can be applied to any multi-channel images. Yu et al. (2015) have developed a technique for determining dust fall distribution in urban areas by integrating remote sensing and ground-based spectral data. They have used MODIS Terra L1B data and measured the sample leaves by a spectrometer (Analytical Spectral Devices Field Spec Pro). They have used back propagation (BP), neural network model, to retrieve the dust fall weight analysis using satellite imagery and ground measured dust data. Ong (2014) has developed a method to detect dust loading from hyperspectral remote sensing data. They have used airborne hyperspectral (HyMap) data and GER-IRIS field portable spectrometer for field measurement. They have found a correlation between dust loading prediction and field prediction. Samadi et al. (2014) have developed a method for the detection of dust storms known as the Global Dust Detection Index (GDDI). They have used MODIS data. They have suggested that this method can be used in dust storm forecasting and warning systems both on the land surface and water bodies.

2.5 Forest health risk assessment and prediction

2.5.1 Forest Health Risk (FHR)

Forest health is a term used to describe the condition of a forest that directly dependent on nature and human activities. A healthy forest is the basis of sustainable forest management. Climate change and intense human activities pose a serious threat to forest health, so more and more attention should be paid to forest health. However, due to climate change and increased anthropogenic activities, the Indian forests are more likely to face the risk of forest health. The term ‘risk’ is defined as the likelihood of damage or loss of forest due to physical and anthropogenic activities (Hanewinkel et al., 2011; Schaberg et al., 2001; Apostolakis et al., 1980). From the literature review, five leading factors have been identified that determine the risk to forest health. They are climate, biotic and abiotic factors, topography, environmental, and anthropogenic factors as well (Oszlányi, 1997; Ramsfield et al., 2016; Alfaro et al., 2014; Zirlewagen et al., 2007). FHR rests on biotic and abiotic disturbances (forest fire, air, soil pollution, droughts, pests, floods, and mudslides), climate factors (changing temperature level, precipitation frequency, atmospheric carbon dioxide change, and extreme climate events), invasive species (spread of species without natural predator) and anthropogenic (road , settlement, shifting cultivation, industry) activities (Pause et al., 2016; Lausch et al., 2017; Trumbore et al., 2015). Some researchers had shown that climate change is the main factor for change in forest health conditions (Latte et al., 2015; Morin et al., 2018). In the United States, forest health gets badly affected by climate change, increasing CO_2 (carbon dioxide), and air pollutions over the last 150 years, and it continues to get affected in the future (Loehle et al., 2016). The change of forest health and plant biodiversity depends on climate change, damage by insects, and species composition. Forest insects play an essential role in decomposing vegetation. They can occasionally kill trees and impact forest health (Yang et al., 2005; Pureswaran et al., 2018). The plant species composition and structure affect health in the forest's entire plant community (Moore et al., 2004; Keeton et al., 2010). The temperate forest of North America was affected by diseases, insect pests, species composition as well as annual burning many times (Van et al., 2015; Dale et al., 2001). Sufficient water supply is necessary for maintaining the growth of a healthy forest. Some researchers have shown an inverse relationship between water availability, temperatures, rainfall intensity, and forest health (Giorgi & Pal, 2004; Vayreda et al. 2012; Toledo et al., 2011). FHR get also affected by drought and flood. These factor in affects the trees growth, disease problem as well as defoliation (Ling et al., 2003; Payn et al., 2015). Soil condition is one of the factors in FHR assessment. Different components of soil such as water, heat, nutrient, mechanical features, and oxygen support the growth of the plants (Bennett et al., 2008; Zirlewagen et al., 2007). Air pollution is one of the main factors that contribute to FHR that would be exacerbated by climate change and other anthropogenic activities (Loehle et al., 2016; Percy & Ferretti, 2004). The mining of minerals activities significantly damages forest health. Kayet et al., (2019a and 2020) had shown that the negative relationship between forest health and distance from mines with foliar dust concentration. The dust has a very detrimental effect on FHR. The air polluted by heavy metals (acidic sulfur and nitrogen compounds) caused risk to forest health (Manning, 2001; Shparyk & Parpan., 2004). Mining generated dust directly affects the tree leaves. Tuominen et al., (2008 and 2009) showed that mining and transportation of materials to dumpsites have a very high-risk effect on forest health.

2.5.2 Remote sensing and GIS application in FHR assessment and prediction

In many studies, the integrated satellite imagery, various model and algorithms with multi-criteria analysis analytic hierarchy process (AHP) based model are used for assessment and prediction of FHR. Some researchers used aerial photographs and narrow banded space-borne satellite data for FHR study (Hyyppa et al.,2000; Castro et al.,2003). They had shown Red and NIR (Near-infrared) bands are better forest health results In many studies, Landsat 8-OLI and QuickBird sensor (Digital Globe-NASA) data were used for mapping forest health risk, and their accuracy levels compared (Wang et al., 2015; Baig et al.,2014). They used the maximum likelihood classification method and shown the QuickBird sensor had better than accuracy Landsat 8 OLI sensor for forest health identification. Ismail et al., (2007) studied forest health using high-resolution (0.5 X 0.5m) multispectral imagery and used a ratio of NDVI (normalized difference vegetation index), Ddifference Vegetation index (DVI), Ratio vegetation index (RVI), and green normalized difference vegetation index (GNDVI) indicators for detection of different crown condition classes of a healthy and unhealthy forest. Meng et al., (2016) studied forest health risk based on textural and spectral information extract from SPOT 5 (Space agency of France) satellite imagery. They ran a statistical model to get FHI (forest health index) map for the Guangxi region. Satellite imagery (Landsat8 OLI and MODIS) and insect and disease survey data had been used for forest health analysis (Housman et al., 2018).They had used change detection methods and shown that MODIS (79.17%) has better forest health results than Landsat 8 OLI (63.48%) data. The USDA (United States department of forest), Forest health monitoring (FHM) program, had developed a model using satellite imagery to assess FHR for the United State's forest. The result showed that a total of 71.7 million acres of forest area are at risk (Alexander and Palmer, 1999). Hyperspectral data provided narrow banded spectral information in

VIR (visible infrared), NIR (near infrared), and SWIR (Short-wave infrared) wavelength regions. This electromagnetic spectrum is used for forest health condition mapping (Solberg et al., 2004; Dash et al., 2017). The narrow banded vegetation indices (VIs) are used in the forest health tool of ENVI to detect forest healthy and unhealthy. Tuominen et al., (2008) and Kayet et al (2019.b) had used this tool for health mapping in mining-affected forest areas and found that NDVI and modified red edge normalized difference vegetation index (MNDVI705) are the main indicators of forest health. Hyperspectral satellite imagery and field-based tree spectral data-based forest health assessment were studied by Tuominen et al., 2009 and Misurec et al., 2012. They had used SVM and SAM algorithms for forest health classification, and shown SVM has better accuracy than SAM. Recently, Light detection and ranging (Lidar) and Drone-based remote sensing techniques have being used for the detection and monitoring of forest health conditions (Anhold et al., 2015; Dash et al., 2017). Those techniques are giving better higher accuracy results than multispectral or hyperspectral data at small scale landscape.

2.6 Summary

The literature review covered under this chapter is related to forest health assessment, identification of tree species, plant diversity estimating, foliar dust estimation, forest health risk assessment, and prediction in the hilltop mining area. It shows that the forest health in hilltop mining areas is always a threat, and scientists all over the world are trying to solve this problem. The literature review shows that several studies have been done on multispectral, hyperspectral remote sensing, GIS-based forest health assessment and its risk prediction. This thesis also highlights a pertinent literature review of spectroradiometer based field spectra applied for the validation of the results.