Centre for Geo-Information

Thesis Report GIRS-2014-17

Assessing Local Expert Data Quality for Forest Monitoring

A Case of Kafa, Ethiopia

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April, 2014

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A thesis submitted in partial fulfillment of the degree of Master of Science in

Geo-Information Science at Wageningen University and Research Centre,

The Netherlands

April, 2014

Wageningen, the Netherlands

Thesis code number: GRS - 80436

Thesis Report: GIRS-2014-17

Wageningen University and Research Centre

Laboratory of Geo-Information Science and Remote Sensing

Acknowledgment

Foremost, I would like to express my sincerely gratitude to my advisor Arun Kumar Pratihast for the abundantly continuous supports, for his patience, motivation, and enthusiasm. His guidance helps me in all the time of my thesis work. My deepest gratitude are also goes to my supervisor Benjamin DeVries who provides me a continuous support and guidance throughout the research. This thesis would not successful without his continuous contributions and supports.

I am also in debt of many individuals for their invaluable contributions. I thankful prof.dr.ir. Arnold Bregt, dr.ir Sytze de Bruin, and Eskender Beza for providing constructive comments and suggestions.

Finally, I personally would like to forward my sincere appreciation to all that were supporting and consulting me through this thesis process. Above all, I thank all my friends, family, fellow MGI student and MGI stuffs for their encouragements and insightful comments.

Abstract

Recent advancement in spatial data collection technologies dramatically increases the contribution of ordinary people to collect and disseminate geospatial data. At the same time, there is an increasing general agreement that community based forest monitoring can play a crucial role in producing and sharing information about the condition of forest resources in time and space. Despite the advantages of the community based monitoring, there are also doubts and concerns that existed in the scientific community related to the quality of the data. Therefore, this research is aiming to assess the quality of forest monitoring activity data sets, which is collected by local experts in Kafa Biosphere Reserve in Ethiopia. The research was conducted to test the quality of local experts data for REDD+ mechanism to track the forest change and carbon emissions. In this research, we examines the quality of local experts data relative to the reference data sets of remotes sensing time series images of 2005 to 2012, GIS data sets, and ground based validation measurements. The main variables are date of forest disturbances, size of the forest disturbance, drivers information, location and coverage of forest disturbances. The spatial variables of the local experts data were assessed using the spatial data quality parameters whereas the temporal variables were compared through BFAST monitoring on Landsat time series images and visual interpretations on high resolution images of Spot and Rapid Eye. The results show that the local experts can perform and produce quality data comparable to validation measurements by experts. We found a regression coefficient value of 0.84 for area/size estimation and ~65% of correctly classification accuracy of drivers information of forest disturbances. Furthermore, the result confirms that local experts have a short time delay in detecting forest disturbances compared to high resolution remote sensing time series data of Spot 5-Rapid Eye satellite images than of Landsat imagery. Based up on the findings of this study, we suggests that the local expert data can enhance the quality of forest monitoring data of remote sensing particularly in detecting near real time forest disturbances.

Key words : Community Based Forest Monitoring; Spatial Data Quality; Local Experts; Time Series Analysis; BFAST; REDD+

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List of Acronyms

Agr. Exp.	Agricultural Expansion
BFAST	Break detection For Additive Season and Trend
CBD	Convention on Biological Biodiversity
CBFM	Community Based Forest Monitoring
CDM	Clean Development Mechanism
CEN	European Committee for Standardization
CFIR	Charcoal and Firewood Collection
EMA	Ethiopian Mapping Agency
EPA	Environmental Protection Authority
FAO	Food and Agricultural Organization
FRA	Forest Resource Assessment
GOFC GOLD	Global Observation of Forest and Land Cover Dynamics
IPCC	Intergovernmental Panel on Climate Change
ISO	International Standard Organizations
IUFRO	International Union of Forest Research Organizations
LULUCF	Land Use Land Use Change and Forestry
Kafa BR	Kafa Biosphere Reserve
MMU	Minimum Mapping Unit
NAT.Dist	Natural Disturbance
PCC	Percentage of correctly classification
REDD+	Reducing Emissions from Deforestation and Forest Degradation
SDTS	Spatial Data Transfer Standard
SDQ	Spatial Data Quality
Sett_Infra	Settlement and Infrastructure
UNFCCC	United Nations Framework Convention on Climate Change
UNCCD	United Nations Convention to Combat Desertification

Chapter 1. Introduction

1.1 Context and Background

Tropical forests are facing pressure from both economic and biophysical factors that causes loss of biomass. This leads to the concentration of greenhouse gases in the atmosphere (van der Werf et al., 2009). In 2007 the UN's Intergovernmental Panel on Climate Change (IPCC) estimated that 17 per cent of global greenhouse gas emissions is released by forest based emissions (IPCC, 2007).Therefore, dynamic information of forest condition needs a proper definition, implementation and evaluation strategies related to multilateral environmental agreements such as UN Framework Convention on Climate Change (UNFCCC) (Frederic Achard, 2013). Consequently, forest monitoring becomes the core of national, regional, international environmental and developmental planning of policies and decisions. It plays a key role for issue related to climate change, conserving biodiversity and sustainable livelihood (FAO, 2012). Furthermore, the UN Collaborative Programs puts forest monitoring in the top global agenda. And, it establishes a multi-lateral initiative on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (REDD+), which is a policy mechanism under the United Nations Framework Convention on Climate Change (UNFCCC)(UN-REDD, 2010). REDD+ aims primarily to reduce carbon emissions from deforestation and forest degradation as well as provides a co-benefits in terms of conserving biodiversity and livelihoods.

Forest monitoring needs a robust, accurate, and consistence methods to estimate the rate of deforestation and degradations(Palmer Fry, 2011; Vine and Sathaye, 1999). More recently, several research has been carried out on different methods that can be employed to estimate forest change within nations and national scale (Asner et al., 2010; Gibbs et al., 2007). Remote sensing and forest inventory are the major ones. The remote sensing community had proposed several methods to measure deforestation using space based earth observation (Achard et al., 2007; DeFries et al., 2005). It is a comprehensive and effective method in monitoring forest disturbance at global and national scale, which enables to estimate the consistent characterization of forest cover change across space and time(Hansen et al., 2010). But, it has not provided accurate estimation of forest changes in small scale forest disturbances such as charcoal production, firewood collection, grazing, and timbering or logging (Achard and Arino, 2012). Furthermore, an integrated approach is critically needed to bridge the gap. As a result, community based forest monitoring is supposed as potentially cheaper approach by engaging local peoples to collect ground based timely data on small scale forest disturbance in order to estimate forest-related emissions(Danielsen et al., 2011; Palmer Fry, 2011). A well-Integration of both approaches can provide much more comprehensive and suitable information to address the forest disturbance than either one alone.

Forest monitoring through local people as experts has been practiced for a long time-line. Recently, it received more attention and acceptances under the umbrella name of community based forest monitoring. It is a monitoring activities that involve local experts who may or may not have professional skill in collecting monitoring activity data about their forests, and who have varying skills and expertise (Evans and Guariguata, 2008). Particularly, when small scale forest disturbance occurred, local experts play a crucial role by providing information about the location, type and time of the forest changes. Many literature reviewed that there are a successful examples, which indicates the feasibility and significant contributions of local experts by collect viable data sets in many developing countries such as Tanzania (Blomley et al., 2008), Philippines (Uychiaoco et al., 2005), Nepal and Mexico(Danielsen et al., 2011; Shrestha, 2011). In addition to this , in the most recent time there are a strong statements and needs from the side of UNFCCC of

REDD+ to involve indigenous local communities in the process of forest disturbance monitoring(Torres, 2013).

Recently, emerging new interactive Open source sensory technologies such as Open Data Kit (ODK) enables local experts to capture geo-referenced data using Smartphone (Hartung et al., 2010; Pratihast et al., 2012). Besides, it also creates an opportunity to acquire forest disturbances data in near real time (GCP, 2012). Within a few days of training, local experts has a capacity of collecting adequate data (Danielsen et al., 2011; Skutsch, 2011). However, there is always a doubt on the quality of the data. As a result, the utility of the data is often unknown. Therefore, there is a need to assess the quality of forest monitoring data collected by local experts. In this study a case study is carried out in Kafa BR, Ethiopia.

1.2 Problem Description

Forest monitoring has becoming increasingly important to quantify changes of forest cover and carbon stocks. This helps to estimate forest based greenhouse emissions. Therefore, decision makers and forest experts requires accurate, timely and reliable information on forest extent, type and changes for monitoring and planning purposes (Bastin et al., 2012).Currently, the advancement in technology that are related to forest geospatial applications has been seen as an opportunity for improving the effectiveness of forest monitoring. Consequently, the increasing use and advancement of geo spatial technology has greatly assisted the exchange of spatial data for forest monitoring (Bastin et al., 2012; Suhaili et al., 2010). Furthermore, the philosophy of spatial data collecting for forest monitoring has been changed from top-down to bottom-up data flow scheme (Joksić and Bajat, 2004; Suhaili et al., 2010). More recently, geospatial data is used in a wide scope of applications via mobile device and other hand held devices by multi-variety users, which involves local experts. This creates an advantage of large collection of data sets, while local experts can particularly engaged and provide field based data. Despite the advantages of local experts, there is a quality issues associated to this kind of data. The gap in expertise and limitations of geospatial data handling of the local experts makes the data liable for erroneous of quality. Furthermore, this leads to the doubt of data quality and its reliability.

Forest monitoring requires accurate, timely, complete and relevant geospatial information. However, forest data is frequently inconsistent and un-harmonized (McInerney et al., 2012). Besides to this, the FRA FAO. (2010) report mentioned that poor data quality and currency are the main concern in forest monitoring. Similarly, the spatial data collected by local experts for forest monitoring in Kafa has also unknown, non-structured and dispersal quality. The data sets, which is collected by the local expert consists mostly a small scale forest disturbance of “deforestations and forest degradations”, and rarely forest enhancements of “afforestation”. It includes both spatial and non-spatial data attributes such as time incidents of the forest disturbance, total area estimations, derivers of forest disturbance , type of forest, locations of disturbances, distances from the roads, and ancillary information of photo and audio (interview of the farmers). Due to the fact that, local experts has a limitation in GIS data handling as well as a gap in expertise, the above mentioned attributes of data are vary or/and disperse in quality. Therefore, it needs consistent assessments of its quality. Also, comparative assessment with the existed reference data sets of national GIS and remote sensing data, and expert validation data is needed. The FGDC (1998) describes data quality as an essential or distinguishing characteristic necessary for geographic data. Besides, the ISO/TC211 (2002) states that “the value of spatial data is directly related to its quality”. Unlike to this, Ferretti et al. (2009) argues that data quality of monitoring is defined by its ability to provide data that allows comparability through space and time. Therefore, there is a need to assess the quality of local experts data using sleeted spatial data quality parameters, while the activity data for forest monitoring is strongly related to the aspects of spatial data. Castro et al. (2013) defines spatial data quality as the measure of the difference between the data and the reality that they represent. Besides, Haklay (2010) states that a quality problem of non-expert (local expert) data could be achieved by comparing against relevant reference data that are presumed to be of higher quality and represents a version of reality. Furthermore, a broad literature is provided on the criteria for evaluating spatial data quality by using parameters such as completeness, spatial accuracy, attribute accuracy, temporal accuracy, logical consistency, lineage, accessibility, usage, purpose (Castro et al., 2013; FGDC, 1998; ISO/TC211, 2002; Oort, 2006; Rasdorf, 2000). However, spatial datasets for forest monitoring may requires selective spatial data quality parameters regarding the spatial data components and aspects of forest disturbances such as time of disturbance, area estimation and derivers information of the forest disturbance. Therefore, in this context, the study was mainly focused on evaluation of the thematic component of data quality as well as completeness of coverage of the existing spatial data collected by the local expert for the purpose of forest monitoring.

The purpose of this study is to assess the local expert data quality of forest monitoring corresponds to the existing reference data of GIS, remote sensing and validation data in Kafa community based forest monitoring. In spite of the scarcity of available validation data, comparative analysis and assessment of data quality was carried out. More specifically, this study helps to determine whether data collected by local experts is sufficiently accurate to measure forest disturbances for robust community based forest monitoring.

1.3 Research Objective

Much concern was devoted to the non-spatial data quality of forest monitoring in the past. In this research we consider the main hypothesis of that local experts can be collect and disseminate accurate and reliable activity data of spatial data sets for forest monitoring, and accuracy of the data sets are assess using the remote sensing data, national GIS data sets and ancillary data sets. The main objective of this study is to assess the quality of local expert data for forest monitoring.

Specific objectives	**Research Questions**
To identify a suitable spatial data quality parameters that will be used to assess the quality of local expert data in the context of forest monitoring.	What are the suitable data quality parameters in the context of forest monitoring to assess the quality of data collected by local experts?
To evaluate the accuracy of data collected by local experts comparing to the existed reference data sets.	What is the accuracy of the local experts data compared with other existing data sources such as remote sensing and national GIS data sets?
To assess the quality of local expert data comparing with ground based validation data collected by experts.	How is the quality of the local experts data vary compared with ground validation data measurements by experts?

1.4 Structure of the Report

Chapter one of the reports presents the general background, the research gap and a description of the problem, as well as the objectives of this study. Chapter two describes the existing review of literatures to give some insights on the previous works. Chapter three focuses on the description of available of data sets used for the test of the case study as well as methodology of the research to execute the research questions. Chapter four includes the results presentation and elaborations. Chapter five and six focused on the discussion and conclusion parts of the reports.

Chapter 2. Review of Related Literature

2.1. Introduction to Forest Monitoring

Forests are a very crucial part of the biosphere influenced the carbon cycle and bio-productivity, which are very essential and the basic foundations for life. However, today's forests particularly in the tropics are under pressure from the increasing demands of land-based products and services that resulted conversion of forests into another forms of land uses. Many study shows that the tropical forests are destroyed at an alarming rate (Achard et al., 2007; Gibbs et al., 2007; Santilli et al., 2005). This causes a sever loss of biodiversity, climate change, and reducing soil fertility , for example, IPCC (2007) mentioned that tropical deforestation and forest degradation are the leading causes of anthropogenic greenhouse emissions, which accounts over 17% of global CO2 emissions. Furthermore, this indicates that clearing of tropical forests leads to destroying important carbon sinks that are currently sequestering CO2 from the atmosphere (Stephens et al., 2007). Therefore, to address these problems there is a need of establishing robust forest monitoring (GOFC-GOLD, 2013). The concept of forest monitoring defined by IUFRO as “the periodic measurement or observation of selected physical, chemical and biological parameters (of forests) for establishing baselines in order to detecting and quantifying changes over time”(Paivinen et al., 1994). Thus, forest monitoring is a systematic gathering and analysis of information in order to determine whether there is an occurrence of forest disturbance. As Evans and Guariguata (2008) describes that forest monitoring is beyond one-time assessment, and it requires a continuous and robust system.

Forest monitoring plays a crucial role for keeping track on deforestation, degradations as well as afforestation over time and space. This enables to observe closely and understand the changes occurred in the forest as well as indirectly provides a law enforcement (Musa et al.).The data collected by forest monitoring provides clear and concrete information to decision and policy makers, governments and other responsible stockholders to take rational action (Danielsen et al., 2005; Holck, 2008; Yoccoz et al., 2001).On the other hand, neglect of monitoring forests can lead sever loss of ecosystem and global climate changes. Recently, deforestation and forest degradation have become an important issue of concerns to mitigate climate change highlighted and addressed in the IPCC (IPCC, 2007). Furthermore, this attracts attentions of various international conventions and agreements on global forest resource monitoring for sustainable forest managements. Global initiatives such as the UNFCCC program established a REDD+ mechanism aiming to mitigating climate changes by reducing tropical forest loss (deforestation) and forest degradation. As a result, establishing robust forest monitoring is undertaken in many tropical countries as a primary mechanism to perform and address the problems by mapping forest disturbances over time. Hansen and DeFries (2004) also argued that forest monitors delivers significant information to predict the changes over time. Evans and Guariguata (2008) summarized in to three main reasons why forest monitoring is becoming important. First, it can help forest managers and users to have concerns about issues such as biodiversity conservation and sustainable management and livelihoods by establishing clear and robust monitoring system. Second, it plays an integral role in the iterative cycle of planning, actions, and assessments of generating information which is used as a catalyst for learning process of forest managements. Third, it can be a crucial mechanism for enforcing compliance with important forest management rules, such as resource access, use, conservation and benefit distribution.

According the argument given by Wulff (2011) the increasing pressures on the ecosystems, climate change, and growing human population are the main reasons that leads to employ more intensive and robust forest monitoring. As a result, the importance of reliable forest monitoring will be likely increase in the future. FAO (2012) also argues that forest monitoring has become a key issue for the future both in the national and international arena of environmental and developmental policy processes and decisions. Furthermore, FAO (2012) described that forest monitoring is a comprehensive process carried out to support decision making processes. It is never an end in itself, but has an explicit serving function in ongoing processes that enables to enhance and monitor changes on forest. Apart from this, most recently, the information provided by forest monitoring activities are uses particularly in mapping and estimating the carbon stock changes. As a result, it also becomes an active domain in research areas and burning issue of discussions in international agreements such as the Rio Conventions of UNFCCC, CBD, and UNCCD.

2.3. Definition of Forests, Deforestation and Degradation

Even though, the terms of forest, deforestation and forest degradation are commonly used, their definition is widely varied among countries, and there is not yet clear common definition. According the FRA of FAO (2010), Forests defined as "a land spanning more than 0.5 ha with trees higher than 5 m and a canopy cover of more than 10 % as well as parcel of land which does not predominantly under agricultural or urban use." Besides to this, the UNFCCC Marrakesh Accords[1] describes as a land area of greater than 0.05 to 1 ha with tree crown cover of more than 10 to 30 % and a minimum height of 2-5 m at maturity in situ, which consist either closed forest formations where trees of various stories and undergrowth cover a high proportion of the ground or open forest[2]. In the Ethiopian context, there is no given a clear definition of forest. However, a working definition has been employed by the FRA FAO 2010, EPA and UNFCCC CDM[3] project defined as a land with relatively continuous cover of trees, which are evergreen or semi deciduous with a minimum of 20 % tree crown cover, area of greater than 0.05, height above 2m, and more than one canopy story (FAO., 2010; MoA, 2013). Similar to the definition of forest, many definitions are existed for deforestation and degradations. Most the definitions for deforestations characterize as the long-term or permanent conversion of land from forest to other non-forest land uses. Specifically, the IPCC (2003) defined as the direct, human-induced conversion of forested land to non-forested land. Moreover, deforestation causes a change in the land cover as well as land uses, and the crown cove should be below 10–30% threshold .On the other hand, Forest degradation defines as a loss of biomass density without a change in the forest cover (i.e. decrease in crown cover that does not fall below the 10–30% threshold or a forest remains forest land and doesn't qualify as deforestation)(GOFC-GOLD, 2013; IPCC, 2003). DeFries et al. (2007b) also describes degradation as a decrease in carbon stock results from human influences, which leads to partial removal of forest carbon stocks.

2.4. Approaches of Forest Monitoring

Forests are a complex system and monitoring of forests needs likewise a certain complexity. Forest monitoring requires comprehensive process of collection, analysis and dissemination of forest-related data at regular intervals to monitoring the disturbances over time. Therefore, it requires approaches and techniques that provide timely, accurate and reliable information. The data acquisition for forestry monitoring can be conducted in many ways, either using field inventories where an experts visit the forest to carried out ground observations and measurements, or with remote sensing where data is gathered from space using earth observation satellites. However, both of these approaches have inherent limitations of data quality. And, the

[1] http://unfccc.int/methods/lulucf/items/3063.php

[2] http://www.redd-monitor.org/wordpress/wp-content/uploads/2009/09/Kyoto_COP001_016.pdf

[3] https://cdm.unfccc.int/Projects/DB/JACO1245724331.7/view

combination of both methods supported by ground based observations are more effective and appropriate to quantify and measure the extent of the forest disturbances (GOFC-GOLD, 2013). Moreover, the recent advancement of technology particularly the growth of mobile and web GIS plays an important role to detect near real-time disturbance.

Table 1. A short summery of opportunities and weakness of the most widely used forest monitoring methods

Method	Opportunities	Weakness	References
Forest Inventory	Accurate estimation of forest structures: volume, biomass, and carbon from tree diameter, species-specific wood density, and height. permanent plot measurements Potential relevant for measurements of timber production.	low accuracy of forest extent estimation Inaccurate estimation using plot to plot in large area/regional basis Time consuming to collect adequate sample plots Spatially limited High cost and intensive trained personnel	Gibbs et al. (2007), Mohren et al. (2012), Gillis et al. (2005), Tomppo and Andersson (2008)
Remote sensing	High accuracy mapping of forest extent or area Les biased measurements Consistent and global coverage including inaccessible area. provides dense time series measurements, which enables to measure disturbances with detail temporal information Near real time detection of forest disturbance Reasonable and/ or cheap cost	Low accuracy mapping of forest structures: volume, biomass and carbon estimation Lack of detecting small scale forest disturbances	Achard et al. (2010), Olander et al. (2008), Fagan and DeFries (2009), Achard et al. (2007),GOFC-GOLD (2013), Gibbs et al. (2007)
CBFM	Detecting small scale forest disturbance (degradations such as loss of biomass, tree volume and extent) Near real time disturbance detection low cost	unknown and discrepancy of data quality	Pratihast et al. (2012), GOFC-GOLD (2013), Palmer Fry (2011), Danielsen et al. (2013) Ferretti et al. (2009)

2.4.1. Forest Inventory

Forest inventory is a means of obtaining information about forest and a systematically collect data for analysis the forest disturbance (Mohren et al., 2012). Mohren et al. (2012) described that “forest inventory is started by mapping forest stands as homogeneous units with regard to species composition, density and size." The term forest inventory is commonly used to describe the technical process of data gathering and analyses of forest. It consists a processes of assessing, interpreting and reporting of forest related data, which is usually conducted from repeated measurements and observations on forest changes over time (LACFC, 2013). In the context of REDD+ forest inventory is described as a data on forest carbon stocks obtained derived from a ground-based plot sampling network.

Forest Inventory methods are used a systematic statistical sampling method to assess forests changes in a large areas(Muukkonen, 2006). More recently, a permanent plot sampling units are used to assess detailed information on carbon stock changes due to the increasing demands of forest monitoring in carbon estimations (Mohren et al., 2012). As a result, a permanent sampling units approach became the most common method of forest monitoring. Thus, has an advantage of repeatedly recorded over time for a plot, which enables measuring forest changes with smaller error (Mohren et al., 2012). Furthermore, the modern inventory concepts combine in situ and remote sensing data for estimation of total biomass, or intercepted radiation (Avitabile et al., 2011). For instance, in most developed countries land use assessment is depend on the merit of ground measurement and biomass stock which is estimated from the national forest inventory. On the other hand, in tropical regions most of the developing countries do not have the technical and financial capacities to assess area of their land using field measurement, as a result, forest inventories are rare and outdated.

According Gillis et al. (2005) forest inventory can provide high quality and reliable data to monitor the forest structure and disturbance through establishing a baselines particularly for a small area and specific measurements like carbon stock change estimation. On the other hand, it is a challenging task to detect forest disturbance in a large area, while it demands a large number of trained personnel, high cost and time consuming to collect an adequate sample particularly this is a challenging for the tropical regions. Apart from this, FAO (2010) recommended that inventory in the tropics is remains questionable due to some measurements are relying on 'best guesses' rather than actual measurements.Tomppo and Andersson (2008) also argued that forest inventory is not a relevant method to estimate the forest disturbance outside the potential area of timber production.

2.4.2. Remote Sensing

Since 1972 earth observation satellites have been providing images with reasonably medium and high ground resolutions that can be used for monitor forest changes. Many research organizations and governments have made efforts to operate satellites in order to monitor the environment such as the forest resources. In the early time of 1970s many researchers assumed that remote sensing data lacks sufficient ground resolution to support forest monitoring. Notably, Landsat TM offers opportunities for forest monitoring through providing a timely and consistent spatial data(Holmgren and Thuresson, 1998). Consequently, the popularity and use of satellite remote sensing in forest monitoring becomes increasingly important. Currently, it is considered as the most reliable data source for estimating changes on forest extents and structure over time (Achard et al., 2007; Olander et al., 2008; Reese et al., 2002). More recently, several high resolution satellites that can be used to detect forest disturbance have been launched and available with free or low cost, quality data, sufficient spatial and temporal details presented in table 2. In the context of forest monitoring, the remotely sensed data by satellites enables to synoptic quantification of forest cover or extent, structure and rate of changes, which helps to determine where and how fast is the forest disturbance occurred (Hansen et al., 2008). Moreover, to detect forest disturbances consistently, it required two or more time series data and detailed-temporal data set (Olander et al., 2008). Many literature showed (for example; (Achard et al., 2007; Hansen and DeFries, 2004; Lambin, 1999)) remote sensing data allows to monitor the extent and rate of forest disturbance by providing consistent methodologies of taking measurements in frequent intervals.

Table 2. Selected optical earth observation satellites and sensors used to monitored forest disturbances at a variety of ground resolutions and reasonable costs.

Satellites and Sensor	Resolution	Minimum Mapping Unit(change)	Cost	Benefits and limitations
SPOT_VGI(1998) Terra_MODIS (2000-) Envisat-MERIS(2004-)	Course Resolution (250-1000m)	10-100 ha	Free or low	Consistent pan-tropical annual monitoring to identify large clearings and locate hotspots for further analysis with mid resolution
Landsat TM, ETM+ Terra-ASTER IRS AWIFS or LISS III CBERS HRCCD DMC SPOT HRV	Medium Resolution (10-60m)	0.5-5 ha	Free and low Landsat and CBERS are free	- map deforestation and estimate area change. - lucks in detecting small scale forest disturbance
IKONOS Quick Bird Rapid Eye (Black Bridge) Aerial Photo	High Resolution (< 5 m)	< 0.1 ha	High to very high $2 – 30 per Km2	- Used for Validation purposes - detecting small scale forest disturbance

Source: taken from GOFC-GOLD (2013).

Generally, there are two widely used approaches proposed by the remote sensing community for detecting and monitoring forest disturbances: Wall-to-wall and sampling methods. In the wall-to-wall methods, remote sensing images covering the entire region are analysed and assessed. whilst, sampling approaches uses a systematic sampling based on regular spaced grid or identify plot locations of forest disturbances across the entire region depends on the topography, soil type, forest type, or degree of disturbance (hot spots)(Achard et al., 2002; Mayaux et al., 2005).The sampling approach provides an estimates of forest disturbance or change on a regional basis. On the other hand, wall - to- wall method provides a measurement of forest disturbance or changes in a country level or full spatial extent of a forest areas. Both approaches offers a possibility of mapping large-scale monitoring such as identifying new clear-cuts and burned areas. On the other hand, the basic attributes of small scale mapping such carbon stock estimation cannot be consistently mapped.

Currently, most of the forest monitoring programs used remote sensing techniques for two main reasons. First, to detect disturbances in the forest extents, which is converted from forest to non-forest land (deforestation) and/or from non-forest to forest land (afforestation). Second, to detect and monitor disturbance within forest remains forest land (degradations), which leads to changes in carbon stocks or biomass loss(Achard et al., 2007; DeFries et al., 2007a; GOFC-GOLD, 2013). There are many course and medium resolution satellites having the ability to view large area with multi-temporal details that provides data for detecting forest disturbance over time. As a result, this dense time series availability of remote sensing data offers a good opportunity to monitoring forest disturbance particularly to detect deforestation. For instance, the Landsat TM imagery provides a good advantage in detecting disturbances with a global coverage of 30m spatial resolution as well as 16-day of temporal details as well as 40-years of historical archive. Similar to this, many course satellite images such as MODIS sensor have also the ability to detect forest disturbances in wide global coverage with excellent temporal details of global or pan tropical forests (Achard et al., 2010). These dense time series imagery enables to measure historical deforestation with sufficient certainty, but there may not efficiently detect and measure a small scale forest degradation(Olander et al., 2008).On the other hand, high resolution satellite imagery such as Spot 5, Rapid Eye, IKONOS, and Quick Bird can provided relatively good to detect forest degradation(Souza Jr et al., 2003). Asner et al. (2005) supposed an ideal way of identify small scale disturbances by analyzing annual time series of high resolution satellite imagery to detect the disturbances transitions. However, this has difficulty of working with the existing optical sensors data while it is not recorded frequently enough with wide area coverage and

Table 3. Accuracy mapping of forest identity or attributes using different earth observation satellites.

<table>
<tr><th>Forest identity</th><th colspan="2">Sensors</th><th>Mapping Accuracy</th><th>Limitations</th></tr>
<tr><td rowspan="2">Area or forest extent</td><td colspan="2">Optical moderate resolution</td><td>80% and above mapping accuracy for the purpose of forest/non forest maps particularly at moderate resolution (~30– 50 m).</td><td>low spatial resolution and lack of detecting detail forest information</td></tr>
<tr><td colspan="2">Optical high resolution</td><td>90% and above mapping accuracy</td><td>High cost and many images are needed to map large area. Low temporal details</td></tr>
<tr><td rowspan="4">Volume, biomass and carbon estimations</td><td colspan="2">Optical high resolution</td><td>40–90% mapping accuracy

for measuring and estimations forest of volume</td><td>See above.

Low accuracy in closed forests

Canopy overlap</td></tr>
<tr><td rowspan="2">RADAR</td><td>SAR</td><td>A general accuracy of 50–95%

And above 80% specifically for estimation of forest volume.</td><td>Limited to low-biomass forests; higher biomass decreases accuracy</td></tr>
<tr><td>InSAR</td><td>30–80% accuracy for forest volume

estimates based on the forest height</td><td>Lack of ground elevation data

prevents global forest height/volume estimation.</td></tr>
<tr><td colspan="2">LIDAR</td><td>A general accuracy of 45–97% and above 80% for forest volume.</td><td>spatially limited sampling, data intensive, and expensive.</td></tr>
</table>

Source : Modified from Fagan and DeFries (2009) also lacks of providing cloud-free imagery throughout the year in many tropical upland and montane environments. As a result, this reduces the number of available time series data that can use to map and monitor the area of forest disturbances (Trigg et al., 2006). According the recommendation of GOFC-GOLD (2013) Landsat-type remote sensing data should be the minimum requirements for monitoring forest disturbances with an area extent of 1 to 5 ha Minimum Mapping Unit (MMU). Similar to this, earlier studies of Leimgruber et al. (2005) and Steininger et al. (2001) confirms that a patches of forests clearing of around 1.0 ha can be detected using individual Landsat scene. Thus, allows assessing the disturbed forest by producing a desired map of forest extent or area to detect and monitor deforestation. In general, remote sensing estimates of forest area have high accuracy mapping , while estimates of forest structure and biomass are very sensitive and less accurate (DeFries et al., 2007a; Gibbs et al., 2007; GOFC-GOLD, 2013; Olander et al., 2008).The capability of remote sensing satellites to measure different forest identity is presented in table 3.

In general, for accurate measurements of forest disturbances, it requires a finer resolution remote sensing data supported by ground-based inventory data. For instance, super imposed Google Earth images provide an excellent source of free viewable high-resolution images. It is also continuously updated, improved to finer resolutions, and is available freely across many portions of the world. Particularly, it has good potential for validation by combining visual interpretation with GIS polygon and point files that can be imported and overlaying in Google Earth (Olander et al., 2008). More specially, to estimate carbon stock changes and biomass loss, it needs an integrated measurement of both deforestation and degradation. Thus, will likely be effective if remote sensing measurement is integrates with ground measurement data from local experts (Gibbs et al., 2007; GOFC-GOLD, 2013).

2.4.3 Community Based Forest Monitoring

Even though, remote sensing technique enables consistently monitoring of forest disturbance at global and national levels, it lacks accurate estimation of small scale forest disturbance such as charcoal production, firewood collection, grazing, and timbering or logging (Achard and Arino, 2012; Hansen et al., 2010). As a result, Community Based Forest Monitoring (CBFM) is supposed as potentially cheaper and robust integrated approach by engaging local peoples to collect and disseminate timely ground based data, which strengthened the remotes sensing approach (Danielsen et al., 2011; Holck, 2008). A well-Integration of both approaches can provide much more comprehensive and suit information to address the forest disturbance (Danielsen et al., 2005; Danielsen et al., 2011; GOFC-GOLD, 2013; Holck, 2008; Palmer Fry, 2011).Besides to this, CBFM provides near real time measurements, which helps to identifies disturbances at early stages. This helps to figure out problems and brought solutions before the problems get out of control.

Recently, in many studies particularly in the UNFCCC texts of REDD+ guidelines and reports, there are a strong statements on the need of involving indigenous people in the process of forest monitoring(Torres, 2013). Consequently, CBFM has been increasingly recognized as a potential approach for effective forest monitoring. The CBFM is a monitoring activity that involves local people as experts who may or may have not received professional training and who have varying skills, expertise, societal roles and interests. It is a continuous process where local forest rangers or amateurs systematically record information about the forest changes (Danielsen et al., 2005; Evans and Guariguata, 2008; Guijt, 2007). CBFM is widely known in the past decade with different terms of participatory forest monitoring such as Locally-based monitoring (Danielsen et al., 2005), Collaborative monitoring (Guijt, 2007), Joint monitoring (Andrianandrasana et al., 2005), Event monitoring(Stuart-Hill et al., 2005).

At this time, policies on sustainable forestry management have received a remarkable focus on the engagements of local communities as a strategy to improve biodiversity conservation, decrease forest based carbon emission and improve local livelihood (Danielsen et al., 2011; Evans and Guariguata, 2008; Holck, 2008; Palmer Fry, 2011). Subsequently, extensive global initiatives are promote and empowered the local experts, which are members of the indigenous communities to involve and devolve in monitoring their forests. For instance, a mechanism known as REDD+, under the UNFCCC discussions, has become the de facto point for international efforts to conserve and sustainably use of tropical forests, thereby to tackle climate change (Gibbs et al., 2007; Olander et al., 2008). As a result, local experts at different parts of the world are working with professionals together under the umbrella name of CBFM. Local experts are providing information about the location, type and time of the forest disturbances, particularly when small scale forest disturbance are occurred, which are difficult to detect through remote sensing techniques. A broad literatures shows that CBFM is successfully implemented, and the local experts are collects viable data sets in many developing countries such as Tanzania (Blomley et al., 2008), Philippines (Uychiaoco et al., 2005), Nepal and Mexico(Danielsen et al., 2011; Shrestha, 2011). Besides to this, Local experts can complement data that may lack by the skills and knowledge of the scientific investigations and can identify quickly areas of forest (Larrazábal et al., 2012; McCall, 2003). In addition to this, Evans and Guariguata (2008) argued that CBFM has an advantages of integrating local knowledge into scientific monitoring, building social capital, empowering communities and local institutions in addition to lowering of costs of data collection and facilitating decision-making. Recent thinking indicates that CBFM can play an important role of near real time forest disturbance detecting as well as timely management interventions. Furthermore, CBFM is more than a way of collecting data , it is also a catalyst for core adaptive forest management(Evans and Guariguata, 2008). A part from this, Danielsen et al. (2013) recommended that a particular attention should be paid to train the local experts. This indicates that there is a lack of accuracy measurements in the activity data collected by the local experts, which affects the quality of the information. Therefore, further study revealed about the data quality level and assessment is needed.

2.5 Integrated Geospatial Information for Forest Monitoring

Recently, technological advancements have been changed the state of storing, analyzing and disseminating forests geospatial information through remote sensing imagery, mobile devices and web maps (Musa et al., 2011). Affendi Suhaili (2010) describes this advancement of technology related to forest geospatial as an opportunity for effective implementation of forest monitoring. On the one hand, it also contributes a vital role in simplify the difficulty of using and producing geospatial data, particularly, the local peoples or communities. Furthermore, this makes them an important actors in the field of forest monitoring by providing geospatial data related to forest in the form of sketch maps, mobile and web mapping, and SMS-based services (Georgiadou et al., 2011). Since forest monitoring requires an accurate and timely geospatial information, a relevant information that are derived from satellite images, GIS data sets, mobile mapping and ground based data needs to be integrate. Geospatial science enables to incorporate these data sets and produces an integrated analysis, which can provide new insights into the interaction of forest monitoring activities. Affendi Suhaili (2010) suggested that by combination of different geospatial information, more tactically effective information could be collected and disseminated. Aguirre-Salado et al. (2013) also confirmed that the integration of remote sensing technology with GIS can give more reliable information of forest dynamics. Furthermore, he argued that robust forest monitoring requires integrated geospatial information. Besides to this, Musa et al. (2011) describes that an integrated geospatial science: remote sensing technology with GIS and ICT contributes an important role in keeping tracks of forest disturbances. For instance, mobile devices or Smartphone apps have played a crucial role in support the activities of CBFM in REDD+ projects in Vietnam and Ethiopia (Hartung et al., 2010; Pratihast et al., 2012).

2.6 Spatial Data Quality

Spatial Data Quality (SDQ) has been an issue of concern in GI Science fields for a long time. Specifically, the growth of spatial data availability from satellites, and an increasing of users from non-spatial disciplines attracts attention of many researchers to focus on SDQ (Change, 2003; Devillers et al., 2010). Oort (2006) mentioned five major reasons to increase the concerns of SDQ in the recent years. First, the increasing availability, exchange and use of spatial data. Second, a growing number of users, which are less aware about spatial data quality. Third, GIS enables the use of spatial data in all sorts of applications, regardless of the data quality. Fourth, Current GIS offers hardly any tools for handling spatial quality. The final and fifth one is an increasing of distances between those who use the spatial data (the end users) and those who are creating the spatial databases. Besides to this,Veregin (1999) suggested that a concern needed from data producers and users perspectives such as tremendously increasing of geospatial data in a wide range of applications through experts and non-expert, and availability free and open geospatial data through World Wide Web and mobile technologies. Currently, even indigenous peoples who may not have geospatial knowledge are engaged in creating spatial data sets through Keyhole Mark-up Language (KML) using Google Earth interface, different web based and mobile devices apps. As a result, the quality of spatial data is becoming a major concern (Sidda, 2009). Oort (2006) and Sonnen (2007) argued that further research on SDQ is still needed for a better quality evaluation and visualization using the latest technologies.

Despite many researches are done in the field of SDQ (for example: (Castro et al., 2013; Morrison, 1995; Oort, 2006)), there is no still clear and uniform definition of SDQ. This is probably due to the fact that the concept of quality is subjective and its meaning is strongly depending on the individuals view. Nevertheless, international standards such as ISO/TC211 (2002) and FGDC (1998) provides a considerable common definition of SDQ as a concept of “fitness for use” and also states spatial data elements that form the concept of quality. ISO/TC211 (2002) defines quality as “the totality of characteristics of an entity that bears its ability to satisfy stated and implied needs.” And also, in ISO/TC211 (2009) described as how well a data meets the specification to satisfy the requirements set forth by the users of particular application. In addition to this, a number of definitions are provided in many literatures. For instance, Veregin (1999) describes that as a function of intangible properties such as ‘completeness’ and ‘consistency’, which is affected by the data production and process. Jakobsson (2002) also argued that the SDQ is the difference between the real world objects and their representations. In generally, there is no existed consensus on a single definition of SDQ, although certain definitions, such as the ISO/TC211 are commonly accepted. Indeed, SDQ is an important component in geospatial applications such as forest monitoring, ecosystem management, urban planning, public health, transportation (Hinton, 1996; Longley, 2002; Richards et al., 1999; Sample, 1994), one should be aware of the data quality while it enables to answer questions like the level of data quality corresponding relevance of the applications. More recently, geospatial science has experienced a significant growth, and at least no book about GI Science (GISc) goes without a content of SDQ.

2.7 Spatial Data Quality Parameters

The importance of SDQ parameters are widely recognized in many scientific literature (Caprioli and Tarantino, 2003; Devillers et al., 2002; Lush et al., 2012; Veregin, 1999). Many of the authors argued that SDQ is defined by its essential parameters. These quality parameters are a means of understanding the overall quality of the spatial data by looking at a small piece of it. ISO/TC211 (2009) suggested that quality parameters plays a significant role to understand the non-quantitative information of the data by describing how well the data meets the required specifications. Similarly, Bergdahl et al. (2007) states that quality parameters are useful to characterize the quality of statistics according a clear rules. Sidda (2009) also described that SDQ parameters gives an insight to made decisions whether the data is relevant for a specific application.

For more than 20 years, international standards have identified different parameters that describing SDQ (e.g. CEN, FGDC, and ISO). Despite some differences had been existed between these standards, there is a general agreement in which the most common criteria often identified as the “famous five”: positional accuracy, attribute accuracy, temporal accuracy, logical consistency, and completeness. Besides, many scholars list a number of various elements that express spatial data quality such as lineage, accuracy(spatial and attribute), completeness, logical consistency, temporal quality, usage, purpose, constraints, variation in quality, meta-quality and resolution (Castro et al., 2013; Oort, 2006; Shi et al., 2004; Veregin, 1999). Recently, SDQ is an active domain of research in geospatial science, as a result, some of these quality parameters might be outdated or replaced by new quality parameters. Therefore, a review below in table 4 is executed only the commonly mentioned parameters based up on the exited literatures.

Table 4.Spatial data quality parameters from different literature sources (painted square represents presence of the parameter)

SDQ parameters	FGDC (1998)	Veregin (1999)	ISO/TC 211 (2002)	Castro et al. (2013)	Oort (2006)	G. DROJ (2009)	Aragó et al. (2011)	M.Noorlander (2013)
Attribute accuracy	■	■	■	■	■	■	■	■
Completeness	■	■	■	■	■	■	■	■
Lineage	■		■	■	■		■	■
Logical consistency	■	■	■	■	■	■	■	■
Positional accuracy	■	■	■	■	■	■	■	■
Temporal accuracy		■	■	■	■	■	■	■
Usage, purpose, constraints			■		■			■
Variation in quality			■		■			■
Meta-quality			■		■			■

2.7.1 Attribute Accuracy

According Guptill and Morrison (1995) attributes are facts about a data that describe the name, location, type and other characteristics of a feature that uses to distinguish one feature form another. Attribute accuracy expresses the accuracy of attributes of spatial data sets. ISO/TC211 (2009) described as “an accuracy of quantitative attributes as well as a correctness of non-quantitative attributes of features classifications and their relationships.” Sidda (2009) described attribute accuracy as an indicator of whether features are correctly classified or not by comparing against the reference data sets. Furthermore, Veregin (1999) discussed that proportion correctly classified (PCC), kappa, user’s and producer’s accuracies, and RMS error as a measurement metric, which is used to assess the overall attribute accuracy and miss-classification information. For instance, if a forest area is classified as grass land, it is an attribute or thematic error and then the qualitative attribute accuracy is low or If 10 % of the forest class is wrongly classified, it is non-qualitative attribute accuracy. On the other hand, if the attribute accuracy is possible to quantified using statistical measurement errors such as RMS error, it is quantitative attribute accuracy.

2.7.2 Completeness

It refers to free of errors of omission or commissions in a datasets, therefore, lacking of data completeness can causes a critical quality problem. Guptill and Morrison (1995) divided completeness in to two sub category to clarify the definition of completeness with regard to data quality; data completeness(an error omission and measurable data quality components), and model completeness(aspect of fitness for use).Veregin (1999) also described completeness as feature completeness, attribute completeness and value of completeness. Feature completes refers to the degree of whether all the required feature of one type in a data set is completed in correspondence to the reference data sets. Attribute completeness expresses the degree of an attribute description of a feature, and Value completeness refers the degree to which values are presented for all attributes. In general, completeness measures a presence or absence of features in a dataset compared to the reference data sets. The excess of data in datasets is defined as commissions errors, whilst absences are describes as omissions errors(Oort, 2006; Sidda, 2009).These two errors can identified either by comparing with the contents of the original data set or reference data sets, or by ground verifications and validations.

2.7.3 Lineage

Oort (2006) describes this in a short and simple way as a “history of spatial data sets”. This indicates that life cycle of data sets from the time of collection to the time of outdated. It shows all the stages of transformation and updates. It provides information of the data sources, publication date, methods of derivations and other production process. Therefore, lineage is considered as an important parameter of spatial data while the descriptions are indicators of the quality. For instance, the descriptions about the property of measurement devices used in field work to collect and process the data can help to understand the potential quality of the data.

2.7.4 Logical Consistency

According ISO standards ISO/TC211 (2009) it refers to “the degree of adherence to logical rules of data structure, attribution and relationships.” Veregin (1999) also describes this as an absence of contradictions in the data set values and attributes. Thus, uses to assess how well the logical relationships between features in the dataset. Furthermore, it provides good information of compatibility during an integration of different dataset in addition to the prevention of spatial data quality problem by avoiding redundancy value.

2.7.5 Positional Accuracy

It is the major data quality parameters mentioned by many authors (for example., Veregin (1999), Sidda (2009), Castro et al. (2013)). It can be easily defined as accuracy of spatial objects position in the real world, but positional accuracy goes dipper and refers to the accuracy of the spatial components that describes the deviation of represented spatial features in a datasets corresponding to the reference data sets or real world.

As Castro et al. (2013) and Oort (2006) described that measurement of positional accuracy depends on dimensionality of different aspects of a features, and distinctions are made between relative and absolute, as well as between vertical and horizontal positional accuracy. Relative positional accuracy describes the accuracy of data compared to other relative data in the same data set that assumed better quality or being true. Absolute positional accuracy describes the degree of closeness of a data in terms of coordinate values in a data sets compared to a coordinate values in a reference data sets with the same coordinate reference system. Similarly, the vertical and horizontal positional accuracy describes the positional accuracy of height or depth and location levels respectively. Veregin (1999) mentioned different statistical measurement or metrics to measure the positional accuracy for a point data sets, but hardly for line and polygon datasets. Root mean square error (RMSE) is the most commonly used to measure magnitude of errors or deviations against the actual locations.

2.7.6 Temporal Accuracy

This parameter receives different concepts and interpretations in many literatures. For instance, Oort (2006) uses the term temporal quality to describes the temporal accuracy of a data sets. Further he argues that this quality parameter is beyond the meaning of temporal accuracy and he included different sub elements. Besides to this, Aragó et al. (2011) also uses the same term on his research to describe the temporal accuracy of a data set. In general, temporal accuracy is the time difference or degree of agreement between the data acquisitions in the data sets compared to the reference data sets or actual time (Castro et al., 2013). Furthermore, it expresses correctness of a temporal quality of feature in data sets. Many authors are classified temporal accuracy in to different components such as temporal consistency, temporal validity, temporal lapse (ISO/TC211, 2002 ; M.Noorlander, 2013; Oort, 2006).Temporal consistencies describes how is correctly ordered the events in a data sets. Temporal validity refers to validity of data with respect to time. And the final component of temporal lapse describes up-to-datedness or timeliness of a data.

2.7.7 Usage, Purpose, Constraints

This parameter is directly related to the concept of "fitness-for-use." It provides a clue about the quality of the data for the users on the potential use of the data sets. Devillers et al. (2010) describes this parameter as "whether the data is used as it was assumed, and how it fits to the needs of the intended". Purpose describes the main target and motivations of why data is collected and what is the intended use. And, Usage describes actual use of the data. ISO/TC211 also makes a distinction between the definition of purpose and usage of the data quality, the intended use as a purpose and actual use as usage. Besides, Constraints describes barriers and problem of all process of data in order to make ready for use such as legal restrictions in accessing and use for applications, high costs, and lack of awareness from users. Therefore, a data set which has a lower constrains shows high fitness for use and also high quality.

2.7.8 Variation in Quality

This parameter is hardly mentioned in many literatures of SDQ. It is ignored in many quality approaches of spatial data contents. As Oort (2006) states that it is defined by CEN/TC287 as homogeneity of quality which tested the uniformity of the datasets. And, named it as "variation in quality". Oort (2006) argues that it is relevant only "if quality varies within the data set." This provides an insight to understand the distribution of quality and reliability of a data sets (M.Noorlander, 2013). Furthermore, it enables the data producer to communicate correctly about the data quality as well as enables the users to assess the fitness for use.

2.7.9 Meta-quality

Meta quality is important quality parameters that describe the quality of quality. Oort (2006) describes that "it provides information on the quality of the quality description". besides to this, M.Noorlander (2013) describe as a cover document that contains descriptions about the quality parameters. However, most of the time Meta quality is described as part of other quality parameters. As a result, it is not commonly and explicitly defined as independent parameters, although, it is an important parameter to evaluate the data quality parameter corresponds to the data sets with respect to the considered quality parameter.

2.8 Assessment of Spatial Data Quality for Forest Monitoring

Lack of quality data is the major problem usually hampering planning and implementations of different projects and decision makings. Where assessment of quality is not well established and implemented, the necessary data will not be available or may not be to the standard and required quality in terms of accuracy, reliability and timeliness. To ensure the quality of a data, there must be a frequent assessments and evaluations to identify and address the quality failures as well as to monitor and control the changes. Loshin (2006) describes that data quality cannot ensure by "one-time effort", particularly geospatial data quality is flawed and changes with time due to many reasons. Congalton (2001) describes two reasons why employing quality assessment on spatial data is very important. First, to know how well the data is correctly represented spatially with in space and time. Second, to provide sufficient quality information in order to use for different applications and combining multiple data sets for different purposes. Apart from this, the increasing uses of geospatial data in decision makings of different disciplines, the reliance on secondary data of spatial data, sharp increasing of non-expert users with very limited expertise in the geospatial domain(Devillers et al., 2005; Goodchild and Li, 2012; Oort, 2006) creates additional doubt and questions about spatial data quality. As a result, to reduce the above associated risk or doubts, there is a need of SDQ assessment. More specifically, spatial data used for monitoring (such as forest monitoring) should be assessed its quality frequently in order to ensure and provide accurate, consistent, timely and complete data. Ferretti et al. (2009) argued that frequent assessment of monitoring data quality is important while monitoring data is defined by its ability of providing good precision level, change detection or trends, and comparability through space and time. Furthermore, SDQ assessment is a crosscutting issue, while errors in monitoring data are results from all the process of data storage, processing and reporting in space and time.

In order to achieve high data quality, data quality assessment is needed to put in place of data quality measures and standards. This leads to know how much it is correct, reliable, and certified relatively free of error. Therefore, spatial data produced by different organizations, experts or non-experts should be evaluated its quality by using the spatial data quality parameters corresponding to the reference data. International standards such as ISO/TC211 (2002) argues that SDQ is described using different SDQ parameters. Furthermore, these parameters are the key components of the SDQ assessments to assure the quality. H.Veregin (1998) argues that the SDQ parameters are a compliance test strategies to determine whether a data sets meets the desired level of quality. As a result, in the past decades a few SDQ assessments are carried out by using SDQ parameters. For instance, Girres and Touya (2010) assesses the SDQ of French open street map dataset using the SDQ parameters of attribute accuracy, positional accuracy, temporal accuracy, completeness, consistency, linage and usages. Beverly et al. (2008) also introduced a 10c-approaches of SDQ assessment which consists ten parameters. Apart from this, SDQ assessment employed out of geospatial domain such as forest monitoring requires selected parameters to assess the quality of geospatial data accordingly its unique characteristics of the data and purposes. The selection and review of the parameters of spatial data quality for forest monitoring is described in Chapter three.

Chapter 3. Data and Methods

3.1 Study Area

Kafa forest is an Afro-montane coffee forests located in the South West highlands of Ethiopia, which is also considered as the origin of Arabica coffee and home of an invaluable genetic resource. It is the last remaining montane cloud forest of wild coffee Arabica, however, due to the alarming rate of deforestation (mainly by Fuel wood collection and settlement expansion), the coffee forest is decline and the wild lives are in risk of danger (Sutcliffe et al., 2012). In the early of 2010, the area was officially registered by UNESCO biosphere reserve with the name of Kafa Biosphere Reserve (Kafa BR). This biosphere is the first Ethiopian BR as well as the first coffee biosphere reserve of the world (Bender-Kaphengst, 2011). It covers an area of more than 760.000 ha, which half of the area is covered by forest (Bender-Kaphengst, 2011). It provides an opportunity to combine conservation and sustainable development of the region. Recently, On-going initiatives are established to decrease the CO2 emissions from deforestation and forest degradations as well as provides a co-benefit to reserve the biosphere and sustainable monitoring of the forest. As a result, a community based forest monitoring has already established with the cooperation of NABU project running under the International Climate Initiative (ICI) of German Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) and Ethiopian regional government Southern Nations, Nationalities and Peoples Regional State (SNNPR). Currently, a community based forest monitoring project is operating under the REDD+ projects[4] that aims to monitor the forest condition at a regular interval by involving local communities.

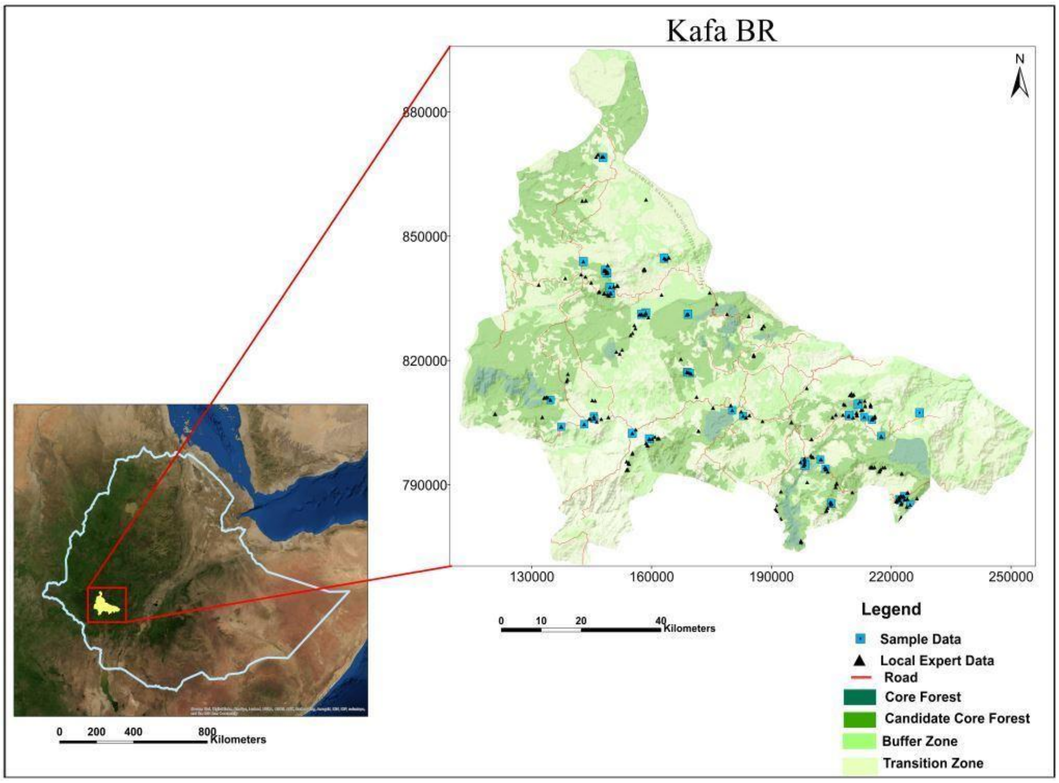


Figure 1. Map of the Study area

[4] http://www.nabu.de/en/aktionenundprojekte/kafa/

3.2 Data Sets

3.2.1 Local Expert Data

This data set is an activity data consists ground based measurements of forest disturbance collected by the local experts or local forest rangers in Kafa BR. 38 randomly selected sample polygons were taken to assess the quality of the data corresponding with the existing reference data sets due to time constraints. The data was collected using Smartphone applications. And, it consists an attributes information of administrative locations, geographic coordinates, type of forest disturbance, forest drivers, incident time of forest disturbance, topography, type and structure of forests, and ancillary information of photo and audio (interviews of the local residents).

3.2.2. Reference Data

This is an existing data sources collected from the national GIS data sets of Ethiopian Mapping Agency (EMA) and remote sensing data of satellite images from different years. Base maps, layers of administrative boundary, roads, village settlements and related data were obtained from EMA. Besides, an archives of satellite data of Landsat TM from 2002 to 2013 , Spot 5-Rapid Eye from 2005 to 2013 and images available in Google Earth were collected for reference of remote sensing. The detail description of the data sets are presented in table 5. In addition to this, The UNESCO Kafa BR forest map collected from Kafa REDD+ project and ancillary information of photo and video (interview) were used as additional reference data sets particularly to identify and asses the drivers of forest disturbances.

Table 5. Availability of data sources used as a reference data from remotes sensing imagery.

Sensor	Ground resolution	Spatial extents	Temporal extents	Remarks/ considerations
Land sat	30m	Full coverage	Full coverage	More relevant for large area/size of forest disturbance polygons
Spot 5	2.5 m (Pan sharpened image)	Full coverage	Full annual coverage of 2011, and partially from 2006 to 2010	Irregular time series
Rapid Eye	6.5m	Full Coverage	Only 2012, 2013	Irregular time series
Images on Google Earth	Superimposed of different satellite images with different resolutions	Partial coverage	Partial coverage	Vary spatial and temporal coverage from place to place

3.2.3 Validation Data

This is a ground based validation data collected by experts for the purpose of validating local experts data. The experts was collected randomly selected 38 forest disturbance polygons used the same method and similar instruments with the local experts. The sample polygons were taken evenly distributed in the study area at different locations, and also targeted and considered the data collected by different individual local experts. Furthermore, this data set was used for comparative analysis of the data quality collected by the local experts.

3.3 Method

The methodology of this research combines both literature reviews and quality assessments of spatial data sets related to forest monitoring data in Kafa BR case study. In order to achieve the research objectives, data quality assessment is needed to put in place of data quality measures and standards. Therefore, in the preliminary stage, relevant parameters of spatial data quality for forest monitoring was identified and selected, which executed in the case study. Subsequently, to know how much it is correct and reliable, a random of 38 polygons of forest disturbance were carried out to analysis the accuracy as well as to compared the quality of spatial data corresponding to the reference data sets of GIS, remote sensing and validation data measurements. An overview of the general methodology is visualized below in figure 2.

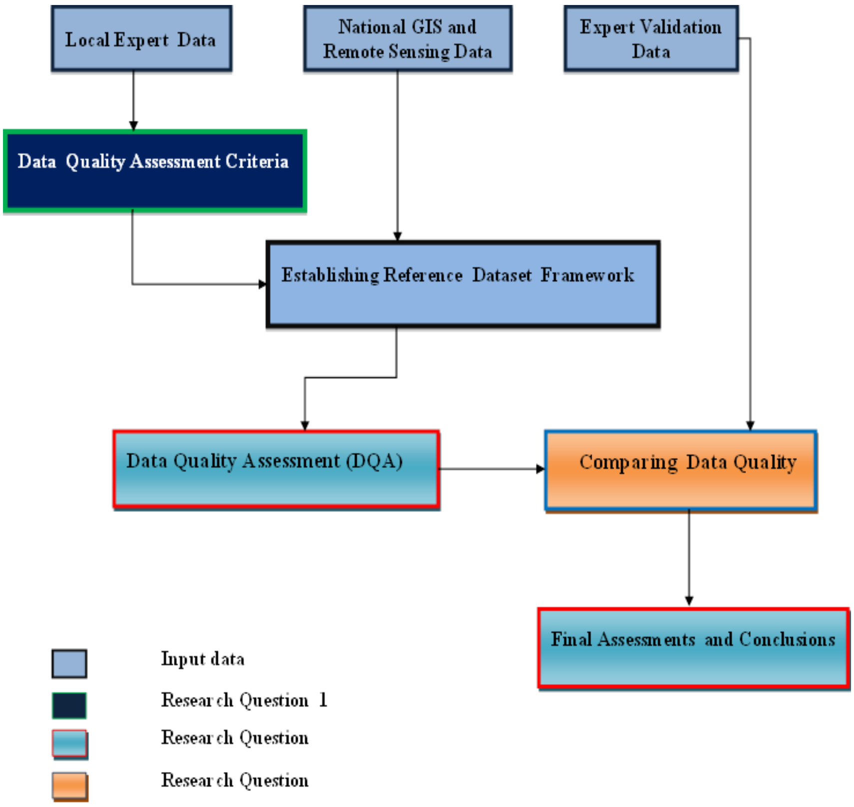


Figure 2. Flow chart model of the general methodology

3.3.1 Selection of Spatial Data Quality Parameters for Forest Monitoring

Forest monitoring involves collection, analysis and disseminating of forest-related data that has both spatial and non spatial components. Forest managers use a variety of geospatial data to assist their daily monitoring activities. For example, maps are used for displaying and analysing forest disturbances and their location. It may also contain additional useful information such as administrative boundary, roads, rivers, and size (ha). Furthermore, forest managers and policy makers utilize spatial data sets related to forest for their decision making supports. And, geospatial science has become a fundamental part of forest monitoring system. On the other hand, the rapid growth of geospatial data both in terms of secondary source data availability and number of users from non-spatial disciplines has increased the concern of SDQ while this heterogeneity of users and uses influences the quality of spatial data sets. Shi (2010) states that many of the existing spatial databases in the recent time are contain errors due to problems on data collection, acquisition sources, and human-technology interaction. Thus, contextualizes the realities on the need and importance of data quality assessment throughout the spatial data cycle using standardized criteria and procedures in different disciplines. Besides to this, Castro et al. (2013) describes that environmental resource monitoring programs has a growing number with a variety of users having limited capabilities and responsibilities in geospatial data quality. Similar to this, forest monitoring based on community collaborations, is more focused on collecting and uploading spatial object or attributes than taking care of the quality. At the same time, many forest managers and professionals are increasingly utilizes the local community generated data to support their own data collection efforts with less attention about the data quality. Consequently, in the recent time a few professionals who could potentially benefit from this data are raised questions and concerned about the quality of such data. This indicates that there is a need of assessing spatial data sets used for forest monitoring. However, there is no existed broad literatures that indicates how to assess the quality of spatial data sets for forest monitoring. Therefore, to identify the appropriate parameters, a review of related literatures was carried out regarding the specific aspects of collected forest monitoring activity data sets. Since this field of research had limited documented research, the review was combined and extended towards the SDQ elements by using different key terms of geo-spatial science(e.g. temporal, thematic, completeness with spatial data quality). Finally, to enable and come up with a reliable answer for the first research question, we were given more insight to the components and variables of the activity datasets collected by the local experts in Kafa BR case study.

In order to examine the quality of spatial data sets of the case study, a selection of quality parameters has been done with regard to the unique aspects of the monitoring activity data set. As a result, some of the quality parameters described in the review literature part was ignored and only the parameters that suit with the collected activity data of forest monitoring were selected. For example, positional accuracy was ignored due to the fact that forest disturbance can't represent with a single point data. Some of the parameters were also excluded due to the limitations of the case study data. Furthermore, while forest monitoring needs a continuous assessment, the nature of the forest monitoring was focused on accuracy assessments of temporal and thematic accuracy. The results of the selection of quality parameters with short elaborations are given below as fellow.

3.3.1.1 Thematic Accuracy

Thematic accuracy is also known as attribute accuracy. Thematic accuracy is the accuracy of attribute values attached to the points, lines and polygons features of geo spatial database that shows how much they are reliable and reasonably correct or free from bias. Indeed, the activity data of forest monitoring is collected both in the form of point and polygon features, which also has definitely thematic components. Rolf (2004) describes thematic accuracy as the attribute values set in a database either qualitative or quantitative data. Besides to this, ISO/TC211 (2002) claims this parameters as the accuracy of quantitative attributes and the classification correctness of non-quantitative attribute encoded in a database and describes the quality of each attribute class. Classification correctness shows the probability level of feature classification in the data set, whether the nominal variables or labels are correct compared to the reference data sets. The quality measure is therefore the percentage of correctly classified (PCC). And also, this can examines mostly by using u of a misclassification matrix, also called confusion matrix and error matrix. For example, 90 % classification correctness for forest disturbance means that 90 out of 100 drivers are classified correctly in the data sets compared to the reference data sets whereas the 10 % classified wrongly. On the other hand, quantitative attribute accuracy describes the accuracy of a quantitative attribute, which is the degree of bias in estimating the values assigned. The quality measure is a probability level in percentage, RMSE or standard deviation. Therefore, thematic accuracy assessment has been an extensive advantage in forest monitoring. Beverly et al. (2008) also argued that forests landscape attributes, such as vegetation types, across large spatial scales collected by participatory mappings needs a thematic assessment of the location values, and the type of forests through the geospatial data quality parameters of attribute accuracy. In this study the thematic accuracy assessment consists location accuracy with regard the administration boundary of forest zones, and the drivers of forest disturbance are the main variables of the activity data sets, which require an implementation of thematic accuracy assessments.

3.3.1.2 Temporal Accuracy

Time is a critical factor in geographic data sets. Some data might be biased over time due to the fact that geographic features are dynamic. Unlike to this, in forest monitoring temporal aspect is an essential factor. Timely mapping of forest of disturbance is very important particularly for estimation of terrestrial carbon balance (Schroeder et al., 2011).The IPCC (2003) frame work suggested that robust forest monitoring needs a continuous improvements on the accuracy and efficiency of the activity data sets. Furthermore, the IPCC's puts accuracy as the major one among the five basic principles of robust forest monitoring with the context REDD+. Thus, forest monitoring requires an assessment of time accuracy of the activity data sets in order to detect and measure forest disturbance. Therefore, an assessment on the accuracy of temporal lagging of the data set, which is used to monitor the status of forests at different times, has a significant role on the achievement of forest monitoring goals. On the one hand, temporal accuracy in geospatial data sets is also the most dominant parameter to assess the quality of spatial data sets. ISO/TC211 (2002) describes as an accuracy of the temporal attributes. And,Girres and Touya (2010) argues that temporal accuracy evaluates the actuality of the data sets relative to the real world change.IPCC (2003) claims that temporal accuracy is very important in forest monitoring while it refers to the time coincidence between the encoded and actual temporal coordinates of features or boundaries. Thus, measures the degree of agreement between the data sets and references temporal coordinates for an entity. In the particular case of this Kafa community forest monitoring, the local experts provides a time attribute of forest disturbance and this data sets are compared their temporal lags from different reference satellite image data sets to ensure the quality of the local expert data sets.

3.3.1.3 Completeness of Coverage

The ANZLIC guidelines[5] for spatial data quality of completeness describes with regard the particular aspects of completeness of coverage, completeness of classification and completeness of verification to assess the extent and range of geographic dataset. Furthermore, Completeness of coverage described as an assessment approach for the proportion of the data available in its entirety. This examines the spatial data coverage completeness for the area of interest. Amhar (2012) argues that coverage of completeness is important in assessing the spatial data quality available for the study area. Besides to this, Girres and Touya (2010) claims that assessing completeness has a significant role for data collected by non-experts due to the biasness of data particularly in rural areas data are missing. Similar to this, detecting forest disturbance in the remote rural areas are also facing the same problem, while the local experts are living in the village communities and have limited access such as distance, topography. As a result, the disturbances that are occurred very far from the villages may not be captured by the local experts. However, forest monitoring activities should be implemented on the field of real situations to monitor the forest. Indeed, geospatial data enables to represent these activities by collecting ground data of the real world. As a result, there is a need to understand and

[5] http://www.giconnections.vic.gov.au/content/docs/anzlic/chap4605.htm

[6] http://blog.sandervanhooft.nl/2009/05/kilil-woreda-and-kebele-the-administrative-divisions-of-ethiopia/

know the completeness of coverage of the spatial data quality. This helps to measure the percentage of collected data covers the area of interest. Thus, essentially expresses what portion of the area of interest is measured.

3.3.2 Accuracy Assessments

To assess the accuracy of the local experts data sets, a more practical and technical approaches were used. In this part of methodology mainly three broad parameters are discussed in details, which enabled to test the case study monitoring activity data. A general methodological flowchart of accuracy assessment is provided below in figure 3. In order to evaluate the accuracy of the activity data sets, initially a reference dataset frame work was established based upon different existing data sources of national GIS data sets from EMA, remote sensing data and ancillary information of photo and audio (interview from the local resident). According the reference data sets assessments of thematic accuracy, temporal accuracy and coverage of completeness was carried out. Furthermore, the GIS layers of EMA were used to build the reference datasets for assessing thematic accuracy of locations and coverage of completeness. The remote sensing data sets were used to build and collect the reference data sets for assessing the temporal accuracy. The ancillary data set was used to assess the attribute accuracy of drivers of forest disturbances.

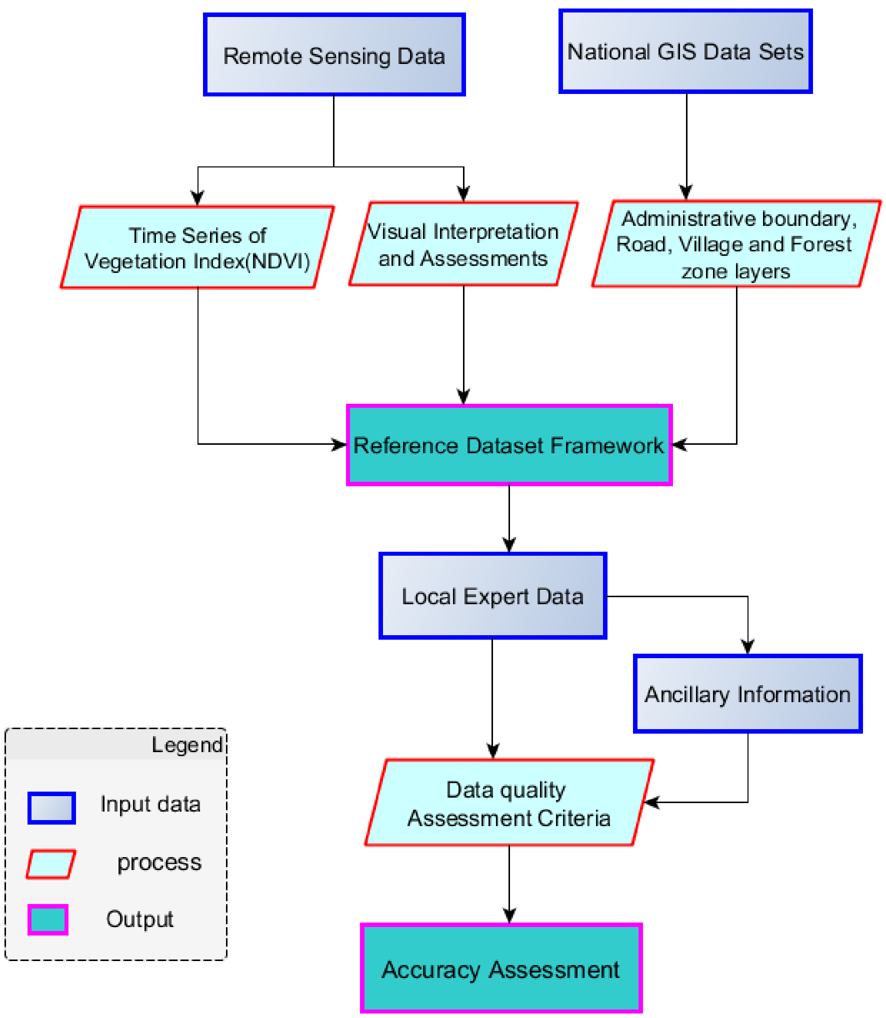


Figure 3. Flow chart model to establish reference framework.

3.3.2.1 Thematic Accuracy

Locational accuracy and drivers of forest disturbances of the activity data collected by the local experts was assessed using the GIS data sets and ancillary data sets.

A. Locational Accuracy: The activity data sets of local experts was assessed whether it is correctly located within the appropriate administrative boundaries based on the references of local administration boundary of Woreda and Kebele obtained from the national GIS layers of EMA. Woreda is an equivalent to district, which is managed by local government, and Kebele is a small unit of local administration that is more similar with neighborhood definition[6]. An over lay analysis using ArcGIS 10.1 was executed in order to analysis whether the reference data sets and the local expert activity data has overlay correctly to determine the percentage classification correctness. To reduce errors which come from the scale difference a tolerance of 1 KM buffer distance was taken in to considerations during the analysis. For instance, if the data collected by local experts is within the distance of 1km distance, it was considered as correctly located as per mentioned by the local experts. Finally, a percentage of locational accuracy was computed by comparing the correctly located local experts data corresponding to the reference data set.

$$\text{Locational Accuracy} = \frac{correctlly\ located\ data\ corrospond\ to\ the\ reference\ data}{total\ number\ of\ collected\ data} \text{ X } 100$$

B. Drivers Classification Accuracy: In Ethiopia, small scale agricultural expansion and fuel wood consumption are the two main drivers of forest disturbances (MoA, 2013).Thus, detecting of these drivers using remote sensing is very sensitive and less accurate (Achard et al., 2010; GOFC-GOLD, 2013; Olander et al., 2008). As a result, the ancillary data sets of photo and interview were used to assess the PCC of the activity data of drivers information. Initially the data relevance and quality of the interview were assessed based on the criteria and assumptions mentioned below and the ranks given in table 6.

To assess the accuracy of the ancillary data sets of audio–interview, a set of assumptions and criteria was defined. The first criteria was set as whether the interview had consists a description about the land cover: forest/non-forest. The second criteria was focused on the explanation about the location and date of forest disturbance. The third criteria was checked if there was an explanation of evidence of about the forest disturbances. The final and fourth criteria was focused on how well the drivers of forest disturbance was explained. Finally, a rank is given for every single interview to compute the percentage of relevance and high quality data.

Table 6. A rank given to the interview of ancillary data sets to categorize the relevance of the data depends on the information provided.

Rank	Description
0	no relevant information
1	fulfils at least one criteria
2	fulfils at least two criteria
3	fulfils three and above criteria

[6] http://blog.sandervanhooft.nl/2009/05/kilil-woreda-and-kebele-the-administrative-divisions-of-ethiopia/

Next to this, the driver information data accuracy was evaluated to determine the classification of correctness. An error/confusion matrix was performed based up on the ancillary data set of Audio–interview compared the local expert data sets. All the audio recorded for every forest disturbance polygons was interpreted and evaluated in order to identify the miss classified drivers. The drivers are classified in to five major dominant categories mainly agricultural expansion, charcoal and fire wood collection, settlement and infrastructure, selective logging, and natural disturbances. Finally, an error matrix was produced to compute the percentage overall accuracy of the misclassifications of the drivers.

Table 7. Error /confusion matrices of drivers information to compute the percentage of correctly classification accuracy of the local experts data with regard to the interview ancillary data sets.

		Reference data(Interview)					
		Agri. Exp	CFIR	Logging	Sett_Infra	Nat.Dist	Total
Local-experts data	Agri.Exp	Ncc					N+c
	CFIR		Ncc				
	Logging			Ncc			
	Sett_Infra				Ncc		
	Nat.Dist					Ncc	
	Total	Nc+					N

Agri. Exp - Agricultural expansion *Sett - Infra - Settlement and infrastructure*

CIFR - Charcoal and firewood collection *Nat.Dist - Natural disturbance*

Overall accuracy = $\frac{\sum_{c=1}^{r} \mathrm{Ncc}}{\mathrm{N}}$ x 100 , *Where: Ncc is the correct classification, N is the total sum and r is the number of row in the matrix.*

Besides, the ancillary photo data set was analyzed by using a qualitative descriptive analysis. This ancillary data set was mainly used to evaluate the drivers of forest disturbance particularly to determine whether the area is covered by forest or not. Initially, the photo taken from all directions (North, South, and East, West and upward) was checked for every single forest disturbance polygon. Then, a qualitative description was executed accordingly whether the area is covered by forest or not as well as whether there is an exited visible driver.

3.3.2.2 Temporal Accuracy

Mapping timely forest disturbance is very important for implementation of robust forest monitoring. However, lack of dense temporal time series reference data set, which covers all temporal detailed of the potential disturbances in near real time is a major challenge (Kennedy et al., 2007; Schroeder et al., 2011). Also, in this research, a dense time series of high resolution satellite images was not available, as a result, to overcome this limitation a multi-temporal medium spatial resolution imagery of Landsat time series from 2000 to 2013 was used in addition to the irregular time series images of Spot 5 and Rapid Eye. The combination of both high resolution imageries of Spot 5 scenes from 2005 to 2011, and Rapid Eye scenes from 2012 and 2013 was considered as one full time series of 2005 to 2013. As a result, the combination of these high resolution time series images was used with name of Spot 5-Rapid Eye imagery in this research. Furthermore, to assess the temporal accuracy, image processing and interpretation of the listed remote sensing data was performed. Finally, using these reference data sets, the temporal accuracy of local experts data was assessed. A total of 38 forest disturbance polygons was taken and analyzed to evaluate their temporal accuracy. Initially, each forest disturbance point collected by the local expert was converted to a square polygon using buffer techniques. A buffer distance of 0.5m was assumed to fulfill the forest definition given by (FAO., 2010) as well as Ethiopian working definition of forest. Based on the extents of the polygons a time series analysis were performed on the Landsat time series data. BFAST Monitoring (Verbesselt et al., 2012) was employed to compute the time series analysis of Landsat imagery based on the Vegetation Indexes (VI) values. On the other hand, a visual inspection and interpretation was performed for the high resolution imagery of Spot-Rapid Eye imageries

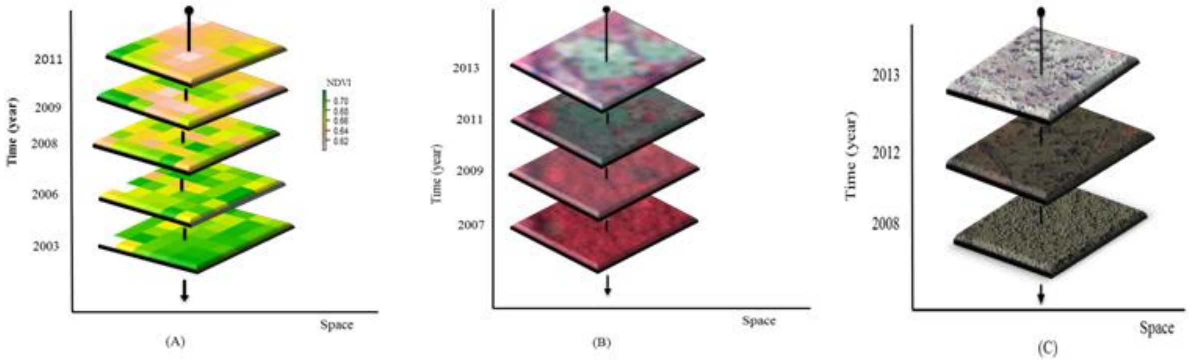


Figure 4.Time series of different satellite images to detect forest disturbance. (A) Landsat time series imagery with NDVI value of between 1 and 0, 1 represents high forest cover. (B) A combination of Spot 5 and Rapid Eye satellite image time series. Red color represents high forest cover. (C) Images available on Google Earth: true color representation.

Initially, an NDVI value was calculated for all forest disturbance polygons from the Landsat imagery between the years of 2000 to 2013. Then after, a time series analysis was executed based on the NDVI value of Landsat imagery. The BFAST Monitoring method was employed to detect the near real-time forest disturbance of each polygons. Even though, BFAST Monitoring detects and provides information on the actual time, magnitude and direction of disturbances, in this research we used BFAST Monitoring only for the purpose of detecting actual time of disturbances and magnitude of changes. BFAST can detects and provides a statistical breakpoint for time of disturbance or change in the time series(i.e. abrupt change) and change magnitude value that shows the NDVI difference between the predicted monitoring value and actual observed values based on the stable history(Verbesselt et al., 2012) presented in Figure 5. BFAST Monitoring is a change detection algorithm used to detect anomalies in time series data related with forest and ecological disturbances particularly in near real-time disturbance detection. It uses a training period or historic stable data to derive normal predict response model and further allows detecting anomalies of breakpoint if there exist a significant deviation or abrupt changes from the predicted model based stable period. A part from this, BFAST has also some limitation. It produces only a single breakpoint and magnitude, and it ignores if there is more than one disturbance in the time series. Another major limitation is it does not produce overall change of the time series trend of entire period.

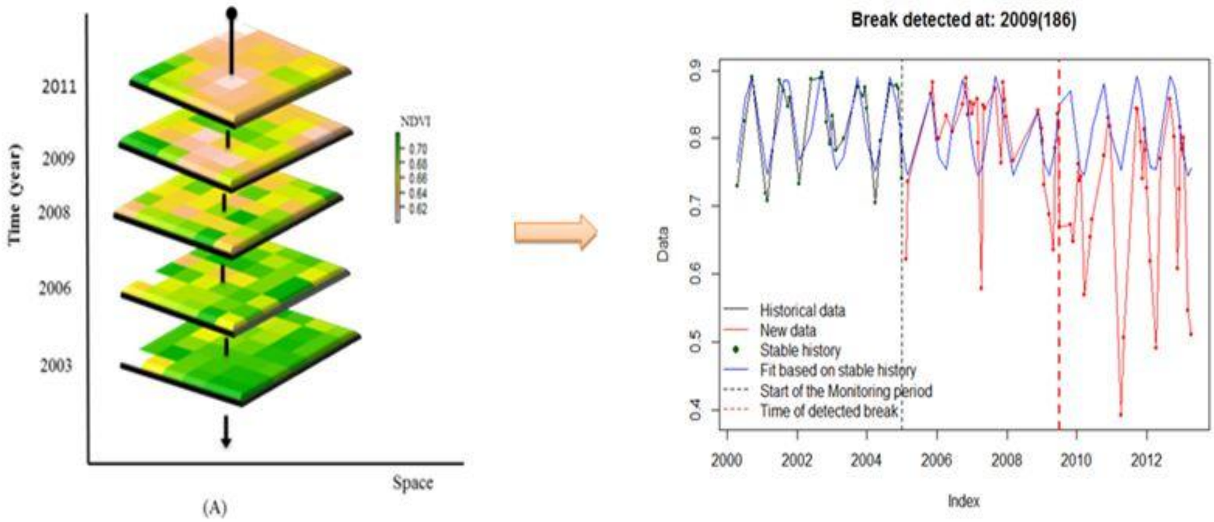


Figure 5. Time series analysis of Landsat imagery between 2000 and 2013.The period from 2000 to 2005 is considered as a stable history period and the period after the simulated break is the monitoring period (grey background). The monitoring period starts from 2005 contain many observations in red line color lines that show the monitoring trends. A prediction of the model is shown with a blue line color which enables detecting the disturbance. Finally, a forest disturbance is detected in a red dotted vertical line at 186th day of the year 2009 and a change magnitude value of -0.0158

Besides, a visual inspections and interpretation of high resolution satellites images of Spot 5-Rapid Eye, and Google Earth was performed to detect the time of forest disturbances. Spot 5 imagery from 2005 to 2011 and Rapid Eye imageries of 2012 and 2013 was combined to gather to considered as a full continuous time series data of 2006 to 2013.The super imposed images on Google Earth were conducted separately while it has possibilities of full temporal coverage from 2000 to 2013. Finally, a visual interpretation of satellite images for each disturbance polygon was executed, and the time of forest disturbance was estimated for each single polygon. Examples is provided below in figure 6 and 7 to show how the time series images are detect a single forest disturbance. Finally, a temporal lag between the reference time series data sets, ground based validations collected by experts and local experts data were calculated to determine the average time delay or temporal lags in detecting the date or incident time of the forest disturbance.

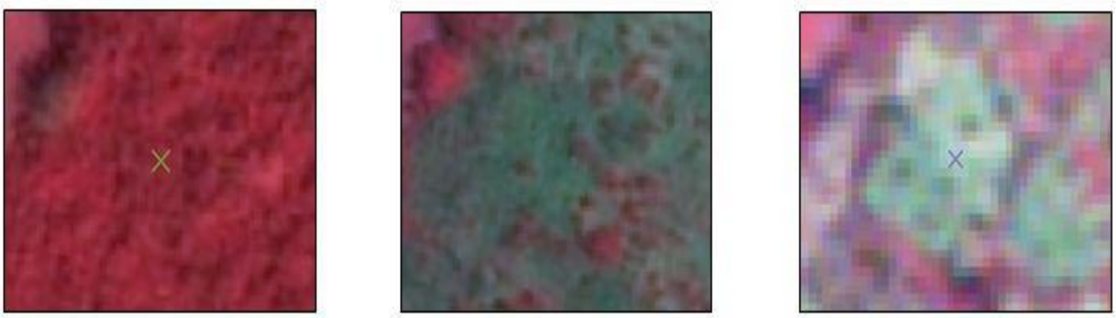


Figure 6. Time series images of Spot 5(left and middle) and Rapid Eye (right) pan-sharped satellite images shows the forest cover change in 2009, 2011 and 2013 respectively. Red color indicates forest cover. The forest was intact in 2009, and it was slightly disturbed and removed in 2011and 2013.

Figure 7. Super imposed satellite imagery on Google Earth that shows forest cover changes in 2008,2012, and 2013 respectively from left to right. The area was covered by forest in 2008, and it was disturbed or removed in 2012 and 2013.

3.3.2.3 Coverage of Completeness

In order to calculate the coverage of completeness, initially an average distance of each forest disturbance polygons from the roads and near villages was calculated. Next to this, a buffer distance of 2.5 Km was computed from every point to calculate the total area covered by the local experts. Finally, the percentage of coverage completeness was calculated according the given formula below. Besides to this, a percentage of the local expert data to the nearby village was calculated to determine how far the local experts are walking away from their villages.

$$\text{Percentage of Coverage completeness} = \frac{\text{Total area covered by the local experts}}{\textit{Total area of the study area}} \text{ X } 100$$

3.3.3 Comparative Analysis of Spatial Data Quality of Forest Monitoring

To assess how the quality of the local experts has been matched to the ground based validation data, a linear regression statistical analysis was carried out. A comparison of area estimations between the local experts and validation data collected by experts was computed by a simple linear regression where locally expert data were used as the dependent variable and the validation data were used as the independent variable. And, linear correlation parameters (r) were calculated, which indicates the strength of linear relationship between the two variables. While the size of forest disturbance might be increasing from time to time, data collection time was taken in to consideration. As a result, in this research only data sets from the same time or year was conducted and compared. Apart from this, to compare the drivers classification of forest disturbance between the local experts and validation data, a confusion/error matrix was performed. The confusion matrix provides a statistical measure that indicates how accurate the local experts are classified the drivers comparing to the validation measurements by expert.

Table 8. Error matrices of drivers information to compared the local experts data with validation data.

		Validation Data						
		Agri. Exp	CFIR	Logging	Sett_Infra	Nat.Dist	Afforestation	Total
Local Experts data	Agri.Exp	Ncc						N+c
	CFIR		Ncc					
	Logging			Ncc				
	Sett_Infra				Ncc			
	Nat.Dist					Ncc		
	Afforestation						Ncc	
	Total	Nc+						N

Overall accuracy = $\frac{\sum_{c=1}^{r} Ncc}{N}$ *x 100 ,where: Ncc is the correct classification, and N is the total sum of the matrix.*

Chapter 4. Result

4.1 Overview of the Local Experts Data

The principal goal of this overview description is to give an insight about the background characteristics of the data, which was collected by local experts in Kafa BR. Furthermore, the purpose of this overview assessment is not to rank the quality of the data sets, but it is aiming to provide information about use of the data sets and provide an internal characteristics of the data sets.

The local expert data consists both spatial and non spatial data sets, which is used to tracking the changes and monitor the forests. Location, date of disturbance, drivers information, evidences of disturbance, current land use, type of forests, and area estimations of forest disturbances are the major variables of the activity data sets collected by the local experts. Figure 8 presents the local experts data and ancillary information of photo for a single disturbance polygon that was collected in Kafa BR. The table in the right column shows that an attribute and value of the main variables filled by the local experts using a Smartphone application for a single forest disturbance polygon. The picture in the middle shows a polygon of the forest disturbances overlay with Spot 5 satellite images. And, the photographs on the four directions shows the deforestations in the real ground towards the north, south, east and west directions. In general, the local experts data has collected an activity datasets to monitoring deforestations and forest degradations starting from 2010 for the purpose of REDD+ project. Majority of the activity data are a small scale forest disturbances caused by small scale agricultural expansions, charcoal and firewood collections, resettlements, road constructions and coffee investments.

Attributes	Values
Location	Tura
Date of data collection	2013
Distance to road	3 km
Distance to near village	0 km
Distance to core forest	2km
Forest type	Natural
Date of disturbance	2012
Evidence of disturbance	Clear catting and logging
Drivers of forest disturbance	Settlement
Current Land use	Crop land (Maize)
Area of disturbances	4 hectare

Figure 8. A general overview of the local expert data sets. The Photo in the right side shows the real picture of the ground and the image in the middle shows the forest disturbance polygon overlaid with satellite images. The table in the right column shows the attributes and values about the forest disturbance.

4.2 Accuracy Assessment of Local Experts Data

The test of accuracy assessment is carried out based on the selected parameters adapted from SDQ elements. Different measurements of accuracy assessments are performs from the forest monitoring data collected by the local experts such as location labeling , drivers of forest disturbance, time of disturbance, spatial coverage. The results are presented as fellow below with short elaborations.

4.2.1 Thematic Accuracy

Here, two main variables of the data collected by the local experts are tested and assessed: locational accuracy and drivers information of forest disturbance.

4.2.1.1 Locational Accuracy

In this category, correctly classified accuracy of the data collected by local experts is carried out based on the GIS reference data of both " Woreda and Kebele" administration labeling and delineations. It is assessed whether the forest disturbance polygon is correctly located in its Woreda and Kebele administration boundaries. As a result, from the total of 38 polygons of forest disturbance captured by the local experts, 36 polygons are classified correctly with regard to the reference map of Woreda location and boundary. The percentage of locational mapping accuracy has produced 95%. This indicates that all most all of the local experts can correctly report the forest disturbance with its correct Woreda locational labeling. Similarly, the forest disturbance polygons captured by the local experts are checked whether it is located and classified correctly within the proper administrative location of Kebele or local area names . As a result, 27 polygons are located or classified correctly with the reference of map and 11 polygons are classified incorrectly. The percentage location accuracy results 71%. This has relatively lower accuracy compared to the Woreda locational accuracy, which indicates that the local experts have a difficulty of identifying the exact location of local area names.

4.2.1.2 Interview Ancillary Information: Drivers of Forest Disturbance Classifications Accuracy

The result shows that 66% of the interview ancillary information has provided a relevant information. On the other hand, nearly 34 % the interview has not provided relevant information. It is either submitted with no information or lacking of meaning full information. Furthermore, 76% out of the relevant information has reported with high quality information , which consists the major information and descriptions of drivers, evidences, location and date of the forest disturbance. From this we can concluded that the ancillary information has still a significant role to provide additional and supportive information.

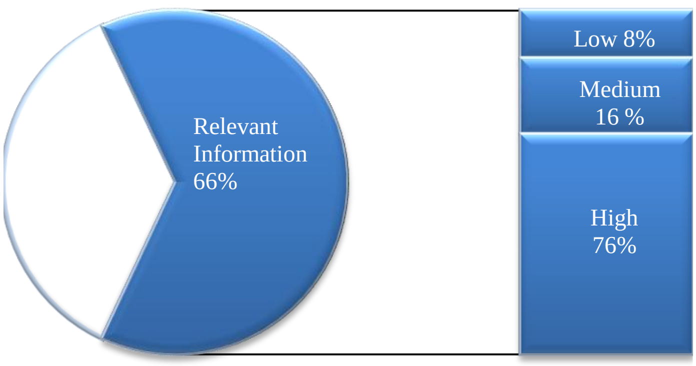


Figure 9. Data quality of interview ancillary data sets

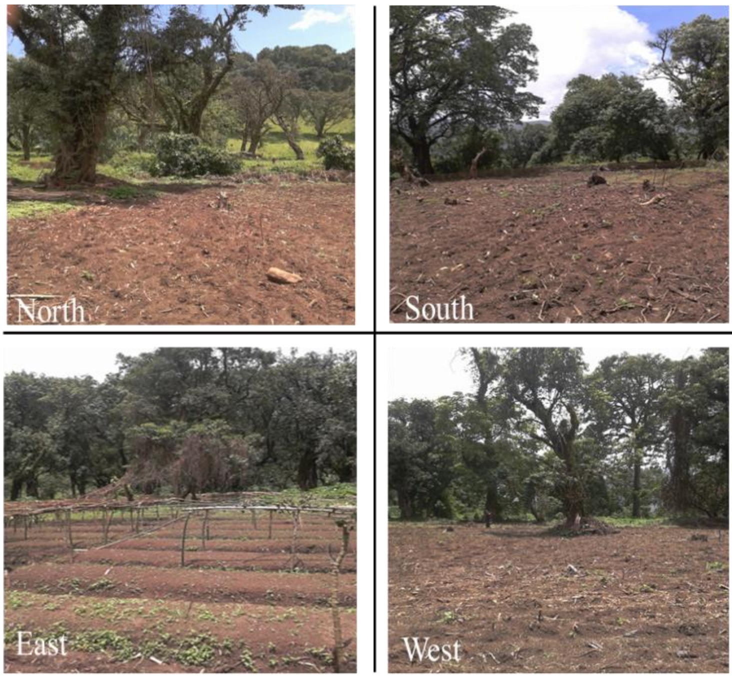
As we seen in the error matrices of table 9 the overall accuracy is produced ~ 83%. This seems a promising result that indicates the potential of the local experts on producing high quality data sets. Furthermore, this indicates that the local experts has a good capacity of collecting and describing relevant information on the drivers and evidences of the forest disturbance compared to the ancillary data.

Table 9. An error matrix of drivers of forest disturbance that shows the percentage of correctly classified accuracy between the local expert data and the interview ancillary data sets.

		Ancilary data(Audio_interview)						
		Agri. Exp	CFIR	Logging	Sett - Infra	Nat.Dist	Total	% User accuracy
Local Experts	Agri.Exp	7	1				8	88
	CFIR		6		1		7	86
	Logging			1			1	100
	Sett - Infra				4		4	100
	Nat.Dist	1			1	2	4	50
	Total	8	7	1	6	2	24	
% Producer accuracy		88	86	100	67	100		
						% overall accuracy		**83**

4.2.1.3 Photo Ancillary Information: Drivers of Forest Disturbance Classifications Accuracy

The majority of the photo provides an additional information whether the area is covered by forest or not, but the drivers and evidence of forest disturbance are relatively complex and difficult to identify from the photo reference. The accuracy of forest and non-forest classification by the local experts according the photo ancillary reference data produced 73 % accuracy that indicates a matched or correctly classify with the photo reference. 18% of the data are classified incorrectly and 9 % are reported without information.



Local Expert	
Location	Oda
Distance to road and near village	1 Km
Type of forest	Natural forest
Is disturbance	Yes
Evidences of disturbances	Clear cutting
Drivers of disturbance	Charcoal and fire wood collection.
Data of Disturbances	24-6-2011
Area estimation	1 hectare

Figure 10. The forest is removed in all directions of the photos. However, The local experts assigned CFIR (collection of fire wood) as a major driver. As we seen in the photographs the major drivers of the forest disturbance seems small scale agriculture expansion. For instance, the photo from the northern direction shows an agricultural land, as well as the other photo shows nursery agricultural land in the east, and a small scale agricultural expansions in south and west directions.

As mentioned above, determine drivers of forest disturbance from the photo ancillary data has difficulties due to the existence of multi-drivers for a single disturbance polygon particularly with the context of the study area. On the other hand, some of the drivers are difficult to identify from the photo such as small scale fire wood collection for household consumption. In general, when we assess the accuracy of forest disturbance drivers collected by the local expert data with regard to the photo reference, it shows promising outcomes with some imperfections. Specifically, the photo ancillary has provides a good additional information about forest coverage and type. Furthermore, some examples of miss classifications between the local expert and the photo ancillary data sets on a single forest disturbance is provided below to show some insights on the quality of the data sets.

Local Expert	
Location	Dukra woshi
Distance to near village	1 Km
Distance to road	3 Km
Type of forest	Natural forest
Is disturbance	Yes
Evidences of disturbances	Selective logging
Drivers of disturbance	Intensive coffee cultivation
Data of Disturbances	25-12-2012
Area estimation	2.5 hectare

Figure 11. As we seen in the photographs the main driver of the forest degradation seems that dominantly charcoal and fire wood collection, and debarking(photo of East). However the local experts reported as ICOFF (intensive coffee plantation) as main driver, while Charcoal and fire wood collection is visible driver in the photographs.

4.2.2 Temporal Accuracy

Initially the percentage of local expert data identified and detected through remote sensing imagery was calculated to show the performance of the remote sensing data sets in the study area. The results shows that Spot 5-Rapid Eye has detected ~88 % of the forest disturbances captured by the local experts and Landsat has detected 75% of the forest disturbances captured by the local experts. On the other hand, Google earth imagery has detected only 19% of the local experts data due to lack of available dense time series images and large parts of the study area is covered by cloud.

The temporal accuracy assessment provides an insight about the temporal data quality of the local experts compared with the existing reference data sets of remote sensing. Furthermore, it provides an information about the suitability of use and internal characteristics of the data sets. The data sets collected by the local experts are compared with remote sensing time series data. Finally, a temporal lag between the local experts and remote sensing data sets is computed to identify the time delay in detecting forest disturbances and the results are presented in appendix A and B.

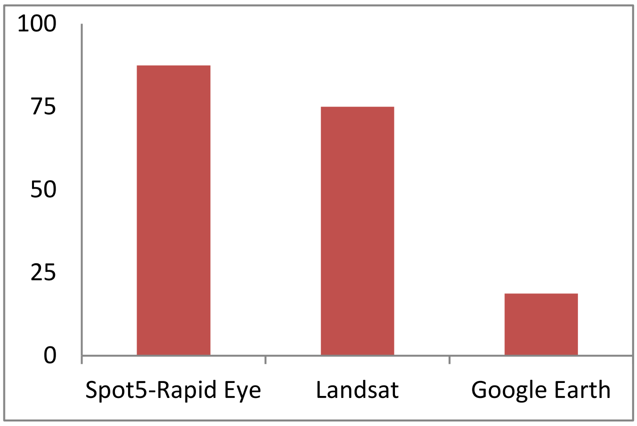
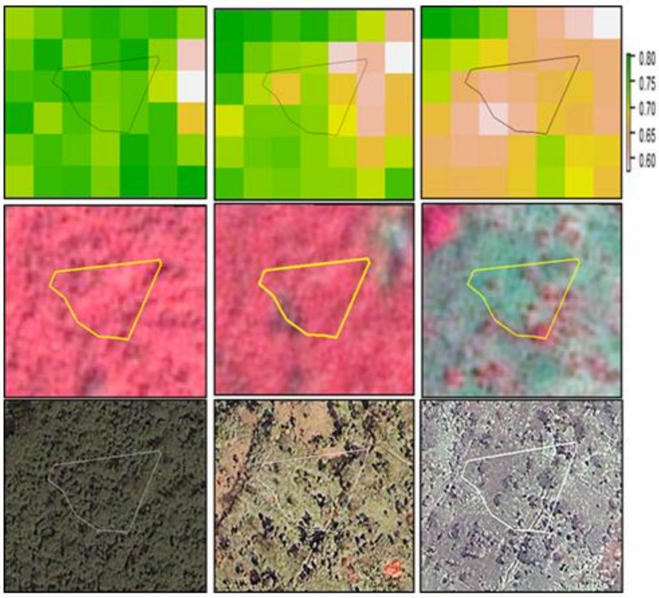


Figure 12. Percentage of local expert data detected by remote sensing time series images.

In figure 13 and 14 a few demonstrations are presented to give some details about the basic attributes and attribute values of local experts data overlay with remotes sensing reference data of Landsat, Spot 5, and Google earth imagery. The figures shows that how the local experts data quality is vary with regard to the reference data sets in detecting forest disturbance. For instance, in figure 13 the date of forest disturbance is detected in 2012 by the local experts, while both Spot 5 and Landsat remote sensing are detected in 2011. Google earth has also detected in 2012, but the time series images of 2009,2010 and 2011are not available for that specific location of the forest disturbance. Similar to this, figure 14 shows a forest degradations starting from 2008 according to the Google earth imagery and 2009 according the spot 5 and Landsat time series images of remote sensing while the local experts are detected delayed by one year in 2010.



Local Experts Data	
Attributes	Values
Location	Tura
Date of data collection	2013
Distance to road	3 km
Distance to near village	0 km
Distance to core forest	2km
Forest type	Natural
Date of disturbance	2012
Evidence of disturbance	Clear cutting and logging
Drivers of forest disturbance	Settlement
Current Land use	Crop land (Maize)
Area of disturbances	4 hectare

Figure 13. It shows a single forest disturbance polygon of deforestation collected by the local experts overlay with different reference remote sensing data sets. The upper row shows the NDVI value of Land sat data in 2009,2010,2011 from left to right respectively. The middle row shows Spot 5 data in 2008,2009,2011 from left to right respectively. The bottom row shows Google earth images in 2008,2012,2013. The table in the right side column describes the attribute data collected by the local experts.

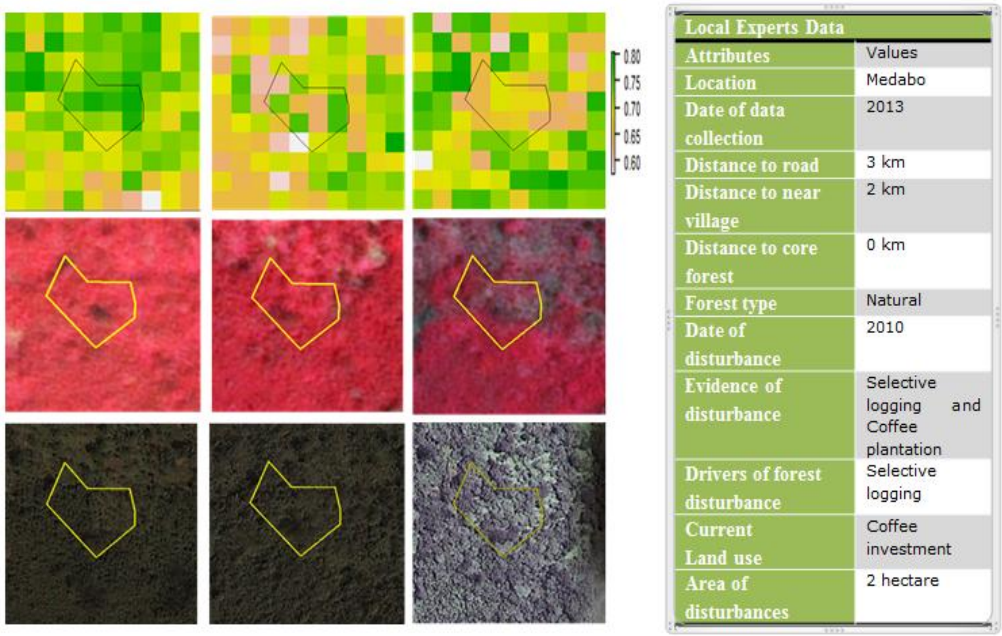


Figure 14.It shows a single forest disturbance polygon of forest degradation collected by the local experts overlay with different reference remote sensing data sets. The upper row shows the NDVI value of Land sat data in 2009,2010,2011 from left to right respectively. The middle row shows Spot 5 data in 2009,2010,2011 from left to right respectively. The bottom row shows Google earth images in 2008,2010,2013 from left to right respectively. The table in the right side column describes the attribute data collected by the local experts.

The remote sensing time series images were used to quantify the temporal lag of local expert data in detecting date of forest disturbances. Table 10 shows the percentage of time delay in detecting forest disturbance between the local experts data and different reference data sets mainly Landsat imagery, Spot 5-Rapid Eye imagery, and validation data. In generally, 45% of the local experts data has a time delay of 3 to 5 years from the Landsat imagery and only 18 % of the local experts data are detected in the same year. Similarly, 48% of the local experts data has delayed 1 to 2 years with Spot 5-Rapid Eye imagery and only 20 % of the local experts are detected in the same year. Apart from this, 48 % of the local experts data are detected in the same year and 36% of the data has delayed 1 to 2 years with the validation data collected by experts.

Table 10. Percentage of local expert data delayed from the reference data sets

Reference data	Temporal lag			
	same year	1-2 year	3-5year	above 5 year
Landsat	18%	23%	45%	14%
Spot5-Rapid Eye	20%	48%	24%	8%
Validation data	48%	36%	4%	12%

In general, the temporal lag between the local experts and high resolution satellite image time series data shows a relatively higher agreement with an average of 1-2 years lag. This indicates that the local experts are delayed 1-2 year to capture the forest disturbance, and also 88% of the forest disturbance captured by the local experts are also detected by the high resolution remote sensing data. On the other hand, the temporal lag between medium resolution Landsat time series data and local experts has shown an average of 3 years lags and only 75% of the disturbances captured by the local experts are detected through Landsat imagery. In conclusion, the local experts and remote sensing time series data shows a time delay in detecting date of forest disturbances particularly the medium resolution time series data of Landsat images. A part from this, the temporal lag between local experts and ground based validation data collected by experts shows relatively smaller temporal lag compared to the satellite imageries. Figure 15 shows that the frequency of the local experts data and temporal lag from the remote sensing time series images. The local expert data and the validation data has shown a higher frequency in zero temporal lag (the same year), which indicates there is higher agreement and lower temporal lag in detecting the data of disturbances. Similarly, Spot 5_Rapid Eye and Landsat imagery has shown a higher data frequency in 1 year and 3 years temporal lag respectively.

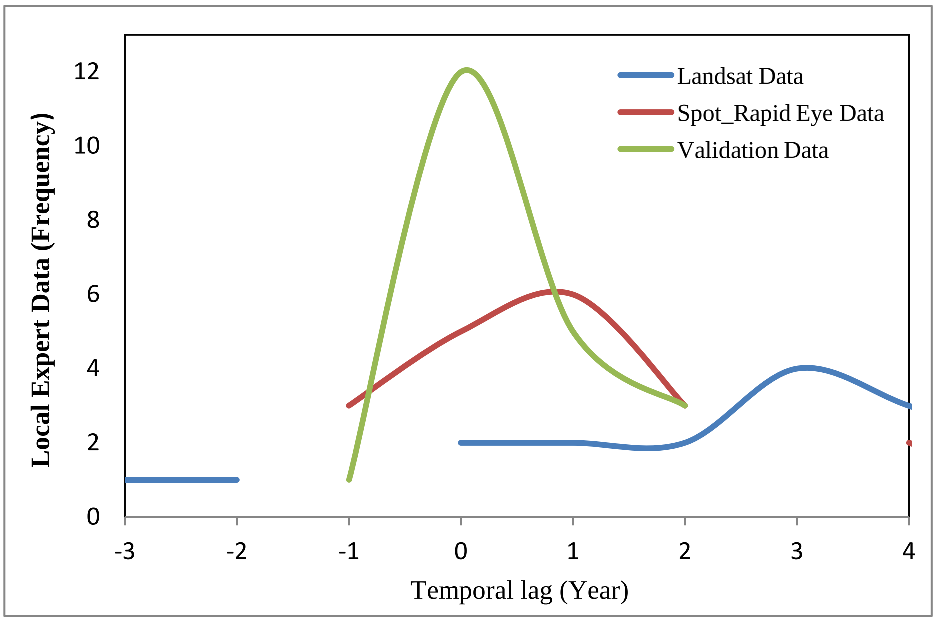


Figure 15..Temporal lag between local experts and remote sensing time series reference data sets of Landsat imagery, Spot 5-Rapid Eye imagery as well validation data. The average time lag is measures in year and plotted in the Y-axis and the local experts data frequency is plotted in the X-axis. The negative value shows that the local experts time is estimated before the reference data set. On the other hand, the positive value shows that the local experts are estimated after the reference data sets.

4.2.3 Coverage of Completeness

The map below in figure 16 shows the area covered by the local experts from the total study area. A total of 1799 Km2 or 179891 ha is covered by the local experts from the total area of 7449 Km2 or 744919 ha in the study area. Only 24% of the study area is visited and covered by the local experts, which is only one quarter of the study area. Besides to this, most of the local experts are collected the data along the roads and town villages. Nearly 65 % of the data are collected within 5km distance or an average of 1 hour walking from the near town villages, 24 % of the data are collected between 5 to 10 km distance from the near town villages, and 13 % of the data are collected with a distance of 10 km and above. This implies that there might be also a disturbance occurred in the remote area, which is not visited and covered by the local experts.

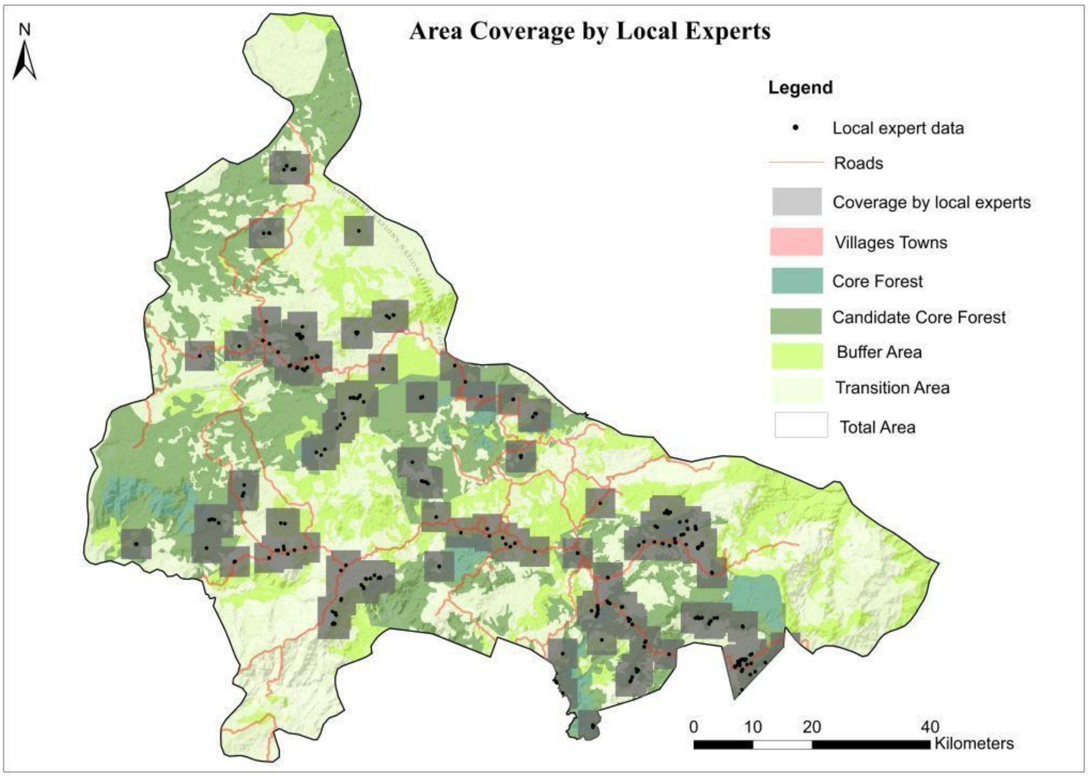


Figure 16. Area covered by the local experts.

4.3 Data Quality Comparison between Local Experts and Validation Data

A statically results are presented below in the figure17 and table 11 respectively to show how the quality of the data is vary between the local experts and validation data in measuring area of forest disturbances and identifying drivers of forest disturbances. Figure 17 shows the comparison of area estimations of forest disturbance using a simple linear correlation among the local experts and validation measurements. The comparison analysis shows that a high agreement between the local experts and the validation data, which results a statistical regression coefficient value of 0.84. This implies a strong correlation between the measurements of local experts and validation data by experts. Furthermore, this indicates the variation of data quality is low.

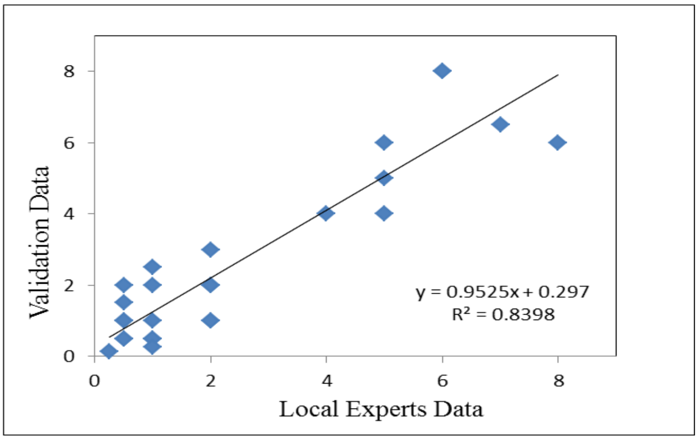


Figure 17. Area estimation between local experts and validation data using a simple linear regression analysis to compare the difference statistically .

Table 11 represents the PCC of driver information about the forest disturbance. The confession matrix consists six columns which represent the reference data sets and 6 rows which represent the test data sets of local expert data. The correctly classified data is presented on the main diagonal of the matrix, which sums up to 24 polygons of forest disturbance from a total of 38 polygons. Finally, the overall accuracy of percent correctly classified (PCC) is computed and the confusion/error matrices produce an overall accuracy of ~65%. This indicates that a relatively good matches among the experts with some defects.

Table 11. A confusion matrix of derivers information about forest disturbance to compared local experts with validation measurements.

		Validation Data							
		Agri. Exp	CFIR	Logging	Sett_Infra	Nat.Dist	Afforestation	Total	% User accuracy
Local Experts	Agri.Exp	8			1	2		11	73
	CFIR	3	5	1	1			10	50
	Logging	1		2				3	67
	SETT_Infra				5	1		6	83
	NAT.Dist					3	1	4	75
	Afforestation		2				1	3	33
	Total	12	7	3	7	6	2	37	
% Producer accuracy		67	71	67	71	50	50		
							% Over All Accuracy		65

Chapter 5. Discussion

Earlier studies conducted by (Danielsen et al., 2013; Danielsen et al., 2011; Palmer Fry, 2011; Pratihast et al., 2012; Torres, 2013) argued that community local experts can collect accurate and reliable data for robust forest monitoring particularly in UNFCCC of REDD+ monitoring. However, most of the study had not taken into consideration about the quality of spatial data sets collected by community local experts. And, there has been very limited information and publications related to the quality of spatial data set (Torres, 2013). In our study, we proposed a parameters adopted from the SDQ elements to assess the quality of forest related spatial data sets. The selected parameters were tested in the case study of CBFM of Kafa BR. Based on the test ,the selected parameters reveal promising results as well as some limitations. In general, our study provides additional evidences that the local experts can collect and disseminate quality spatial data on different variables of the forest disturbance such as location, area estimation of forest disturbance, date of forest disturbance, and drivers information. Here, in this chapter only three basic parameters are discussed below mainly attribute accuracy, temporal accuracy and coverage of completeness to evaluate the quality of the activity data sets collected by the local experts. Besides to this, a comparison of data quality is discussed among the local experts data and ground based validation data collected by the experts.

5.1 Accuracy Assessment

5.1.1 Attribute Accuracy

The preliminary step in the process of forest monitoring is mapping of forest disturbances using the geospatial technologies to know the spatial location of the disturbances. In our study, we found higher accuracy of locational mapping with regard to reference data sets of boundary base maps of Woreda or district level, but it decreases the accuracy with large scale mapping of Kebele or local level. The percentage correctly classification results high mapping accuracy by locating the forest disturbance with its proper Woreda administration level compared to the Kebele. Obviously this was similar result as expected while most of the local experts knows and aware about their Woreda name and location during data collection. On the other hand, the accuracy classification correctness with regard to the Kebele or local administration level shows a relatively lower mapping accuracy. This might be due to the following possible reasons. Since the boundary line is not clearly visible on the ground, the local experts are miss-informed and labeled wrongly when they are around the boundaries particularly when the local experts are away from their own villages. Besides, the local experts may not aware and use of Ethio-Woreda/Kebele reference base maps during field work, which is provided and prepared by EMA and regional governments. Another possible error might be related with human element of data entry errors using the Smartphone devices. This is a crucial question with regard the skills and experiences of the local experts in using of electronic devices or technology particularly with the Smartphone applications. As Pratihast et al. (2012) mentioned in Vietnam CBFM, local forest rangers are less accurate in entering text information manually. Similar to this, Torres (2013) findings from Mexico CBFM indicates that local experts may easily use electronic devices in the field to register data ,which is programmed in advance rather than entering manual texts and information. Apart from this, devices errors such as the degradation of GPS accuracy might be shift the coordinate from the actual forest disturbance location due to the signal blockage by heavy forests, cliff and terrains (topography). Finally, the scale of the reference map of administration map can also be possible source of errors.

Quality of drivers information is another variable, which is tested in this study using classification correctness accuracy. Understanding this quality can provides an essential information to design and implement strategies and policy for robust forest monitoring (Kissinger et al., 2012). Here, we found correctness classification accuracy of 83% relative to the audio-interview reference data sets. This confirms that the local experts have provided a good quality of data compared to the audio ancillary information data sets. On the other hand, assessing drivers from the ancillary photo reference data sets shows discrepancy and subjectivity to assess the quality. The potential reasons that makes difficult to assess the quality of drivers from the photo reference is the occurrence of multi-drivers in single disturbance polygon. For instance, the photo taken from all directions (north, south, east and west) shows different drivers, which mislead and complicated to determine the dominant and historical driver of the disturbance polygon. However, a certain sacrification of accuracy or introduction of errors doesn't necessarily mean the data are not useful. And, we can conclude that the ancillary information has still a significant role by providing additional and supportive information for the local expert data sets (Schroeder et al., 2011).

5.1.2 Temporal Accuracy

Here, assessing the temporal accuracy of data sets collected by the local experts was heavily depended on the quality of the reference data sets. For instance, the resolution and capability of satellite imagery to detect small scale forest disturbances has a significant impact while comparing date of detecting forest disturbance. In general, our result confirms that high resolution remote sensing time series data had better temporal accuracy than of the medium resolution remote sensing time series data. Thus, our finding gives additional evidences that small scale forest disturbance monitoring typically requires fine-temporal detailed information (GOFC-GOLD, 2013; Hansen et al., 2013; Kennedy et al., 2010; Schroeder et al., 2011). Even though Landsat time series images had better possibility of detecting forest disturbances with regard to the advantages of dense time series data availability, it has shown relatively lower agreement and long time delay with the local experts data than of the irregular time series images of Spot 5-Rapid Eye. One possible reason for this could be low spatial resolution of Landsat imagery (30 m) can be a major obstacle to detect small scale forest disturbance polygons. While the size of the disturbance decreases, the ability of the satellite to detect disturbance is also diminished. Kennedy et al. (2007) founds that when disturbances are less than 2 hectare in size, mapping errors are becoming high and accuracy becomes diminished. Indeed, most of the disturbances captured by the local experts are small in size, the possibility of captured by Landsat imagery might be also lower. Besides, Schroeder et al. (2011) founds similar temporal lag with this research findings that is 3 to 4 years time delay to detect fire and partial clearing of forest disturbance. Similar to Landsat imagery, there are also some potential reasons for the temporal lag occurred between Spot-Rapid Eye time series imagery and local experts data. The gaps in data availability due to the infrequent image capturing and irregular time series extended by cloud cover are the major factors in detecting near real time forest disturbance through Spot 5-Rapid Eye. Masek et al. (2008) argues that a significant amount of forest disturbances nearly 30-60% cannot be mapped due to the long interval irregular image acquisitions of imagery . Besides to this, Spot 5 imagery has also difficulties of capturing small scale forest disturbance such as firewood extraction, and selective logging (GOFC-GOLD, 2013; Pratihast et al., 2012). A part from this, our results also confirms that local experts can produces data sets as accurate as experts. We found that the local experts have less than 1 year time lag with the ground based validation data collected by experts. In general, according the results of this study, the temporal data quality of forest monitoring collected by local experts is relatively accurate and reliable. Furthermore, thus implies that local experts may enhance the remote sensing data through detecting small scale forest disturbance particularly this might also provides an insight of local experts contribution with regard to the near real time of forest disturbance monitoring, which is the vital component of robust forest monitoring.

5.1.3 Coverage of Completeness

A coverage of completeness was carried out to assess the quality of the data collected by local experts. Our result reveals that only one quarter of the study area was covered. Besides to this, most of the local experts data were collected near the villages and roads. This indicates that majority of the local experts are walking a short distances from their villages to collect data and monitor the forest disturbance. However, in the Ethiopian context forest disturbance is prominently occurred relatively at remote location or places away from the village towns, market centers and road network system. A study conducted in Jimma zone, South Western of Ethiopia shows that the percentage of forest cover is higher around the roads and town villages, and decreases in the remote locations. Thus, indicates that the disturbances are occurred in the remote locations (Getahun et al., 2013) due to poor farmers in the scattered remote places are completely dependent on the forest to generate their income and livelihood (Gobeze et al., 2009). Besides to this, a global forest change data sets of the study area conducted from 2000 to 2012 by Hansen et al. (2013) confirms that the forest loss was predominantly occurred in the remote locations. In addition to this, a map of forest disturbances detected by BFAST Monitoring in 2012 and 2013 confirms that most of the disturbances are occurred relatively far from the village towns. A sketch map of local experts data and BFAST Monitoring results are provided below for visual inspections.

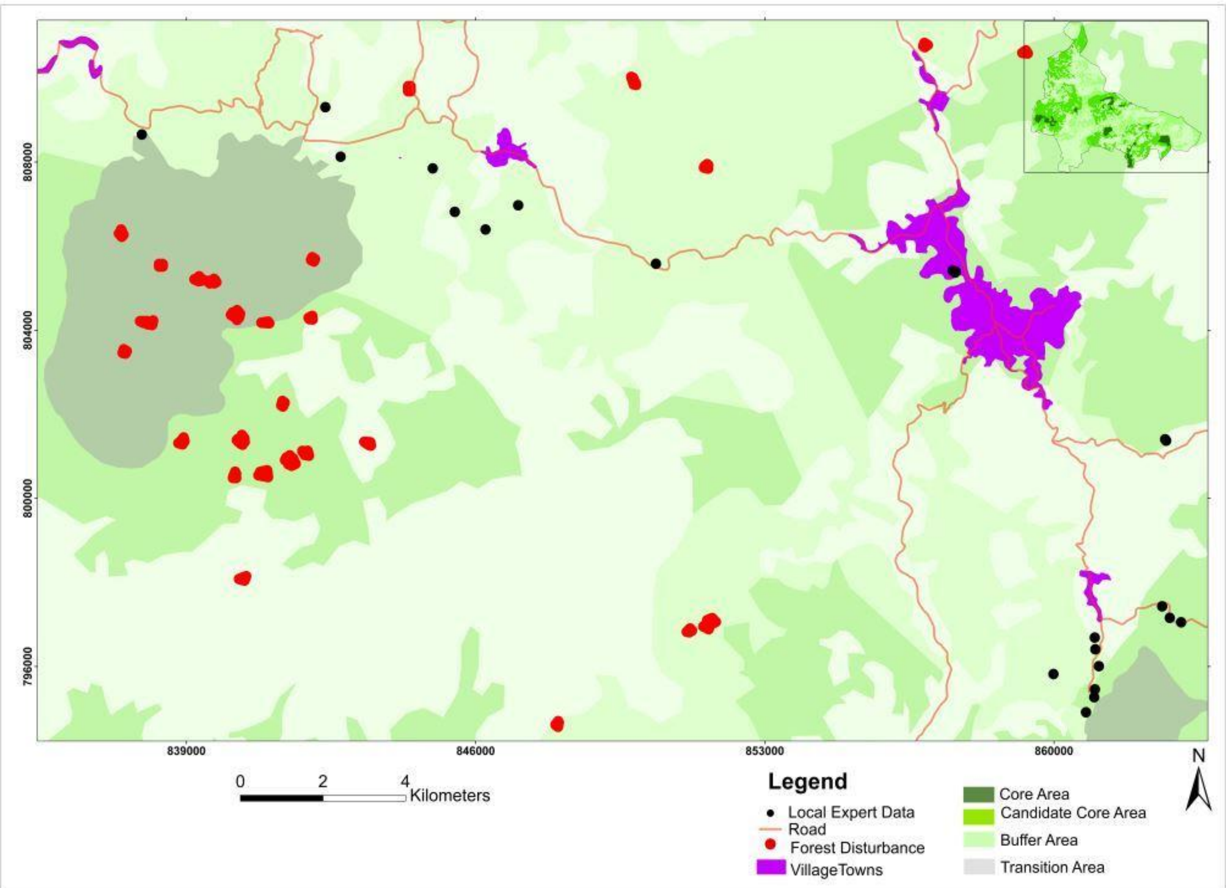


Figure 18. Map of forest disturbances in 2012 and 2013 from BFAST monitoring and the sketch of forest disturbances collected by local experts data in Kafa BR.

5.2 Comparison of Data Quality between Local Experts and Validation Data

Our finding shows data quality between local experts and validation data are similar in estimating area or size of disturbed forest. Similarly to this, various studies (Danielsen et al., 2013; Palmer Fry, 2011; Pratihast et al., 2012; Skutsch et al., 2011) also shown that local experts were collect accurate and quality data as experts in size estimations and locations of forest condition. On the other hand, the data quality of driver information of forest disturbance has a discrepancy, which indicates a relatively low disagreement between the local experts and validation data collected by experts. One possible major reason for this disagreement could be the difference on perceiving the underline drivers of forest disturbances evidence(MoA, 2013). Another possible explanation for the discrepancies could be due to complexity and difficulty of identifying one major driver, while in Ethiopia forest disturbance are typically occurred in the form of small scale mixed drivers and very dynamic. Many drivers could be existed simultaneously in one small forest disturbance polygon due to the fact that most of the people living in the Kafa BR rely on the forest resources for their subsistence livelihood (Gobeze et al., 2009) such as fuel wood consumption, and small scale farming, which are also the most prominent direct drivers in Tropical Africa as well as in Ethiopia (Kissinger et al., 2012; MoA, 2013). For instance, drivers by small scale grazing, and firewood collection could be occurred parallel in a single disturbance polygon or area. A part from this, the time of data collection could be a potential factor while the evidences of drivers and land uses are dynamic.

Chapter 6. Conclusion and Recommendations

6.1 Conclusion

More recently, the role of spatial data is exponentially increasing for analysis forest changes as well as detecting timely forest disturbances. Consequently, there is a need of concern about the quality of the spatial data throughout the whole processes and various steps in space and time. Furthermore, assessing the quality of the spatial data sets is becoming a crosscutting issue. Failure in doing so will render results questionable and disrupt the confidence of data quality. This research has presented the quality of the spatial data sets collected by local experts for the purpose of robust forest monitoring. An assessment of quality on various variables of forest monitoring activity data has been performed using a selected parameters of spatial data quality related to forest monitoring. The result reveal some evidences and limitation in assessing the quality of spatial data sets for forest monitoring. Moreover, the quality of the monitoring activity data sets, which is collected by the local experts is highly depending on the quality of the reference data sets such as mapping scale of GIS layers and the capability of remote sensing time series data to detect small scale forest disturbances.

Attribute accuracy, temporal accuracy and coverage of completeness are the major parameter used to test this study. These selected parameters provides an insight to assess the internal characteristics of the spatial data sets through measuring the main variables of forest monitoring. Our findings confirms and provides additional evidences that local experts can monitor forest disturbances with accurate and acceptable data quality. Moreover, in many circumstances the accuracy of local experts data can also fulfill the data quality standards. The local experts data reveals a higher location mapping accuracy. Besides to this, it shows relatively better temporal accuracy and higher agreement in date of detecting forest disturbance with high spatial resolution than of the medium resolutions time series data. Thus, indicates the local experts can provide accurate and timely data to monitor the forest disturbances particularly in detecting very small forest disturbances such as small scale agricultural expansions and forest degradations caused by charcoal and fire wood collections. On the other hand, most of the data was collected merely along the roads and near town villages. As a result, only one quarter of the study area was covered by the local experts to monitor and detect forest disturbances. Apart from this, the local experts has similar potential to measuring forest disturbances variables compared to ground based validation measurements collected by experts. For instance, we obtained a regression coefficient value of 0.84 in area estimations of forest disturbance between the local experts and the validation data. Similar to this, nearly 50 % of the local experts has detected forest disturbance in the same year. Thus, indicates that the local experts can collect and provide data with acceptable level of quality for robust forest monitoring.

In general, the local experts data is not necessarily inferior compared to professional experts or foresters to monitoring forest disturbance in terms of the overall quality of location mapping accuracy, area estimation, date of disturbance. Potentially local experts data may also be superior in terms of detecting near real time forest disturbances. Furthermore, there is a need of further researches, while comprehensive data quality assessment have the potential to enhance data quality, which in turn would allow an effective robust forest monitoring. On the other hand, the knowledge gained from such research is vital in addressing the capacity gaps currently present in countries participating in REDD+. In addition to this, CBFM can result more rapid management interventions integrated with national forest monitoring and remotes sensing approaches. On the one hand, it may also creates a strong cultural integration and learning process for adapting robust forest management.

6.2 Recommendation

Based on the findings of the reviews and the case study performed, the following recommendations are made:

- The form design of the Smartphone application used by the local experts to collect ground based data should be very simple and programmed in advance by providing an options of selection tabs rather than manual entry texts and information.
- Based our observation and findings related to the ancillary data quality of interview and photo, a particular attention should be paid to give additional training to the local experts of the community members on how to use the Smart phone devices to record audio interview and take photo specifically towards the central point of the forest disturbance.
- To know the exact locations of the forest disturbances and area descriptions, the reference maps provided by EMA and other base maps should be used during ground based data collections in the fields to reduce accuracy errors.
- Since most of the forest disturbances in Ethiopia particularly in Kafa BR are small scale disturbance, archives of high spatial and temporal resolution time series imageries are recommended to be used as reference data sets. Dense time series and cloud free high resolution reference data such as Rapid Eye, ESA's Sentinel series imagery, IKONOS etc. could be a possible source. These data sets should be also support by ground data validations in order to accurately detect and estimate the small scale disturbances such as firewood collection and selective logging.
- To improve the coverage of data collection, more local experts should be involved particularly peoples living in the remotely scattered villages. Apart from this, data collection using SMS text massages using phones which are not supported the android system should be integrated with the existed community based monitoring system to increase the data availability and coverage.
- Since both approaches of CBFM by local experts and remotes sensing have their own inherent limitations of data quality, more work is needed to integrate both approaches taking the advantages of the recent technological advancement such as web and mobile GIS to detect forest disturbances in near real time.
- Due to the time constraints a randomly selected sample data were used to examine this study. However, in the future studies a larger sampling size should be carried out for comprehensive quality assessments of such datasets.
- The monitoring activity datasets collected by the local experts can give a co-benefit to maintain and monitor biodiversity. Further study should be carried out to explore the capability and the links between the ongoing community based forest monitoring and biodiversity monitoring in the study area.
- Finally, further research is recommended to identify and adopt more forest related spatial data quality parameters to assess and evaluate the quality of data collected by non-experts.

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Appendices

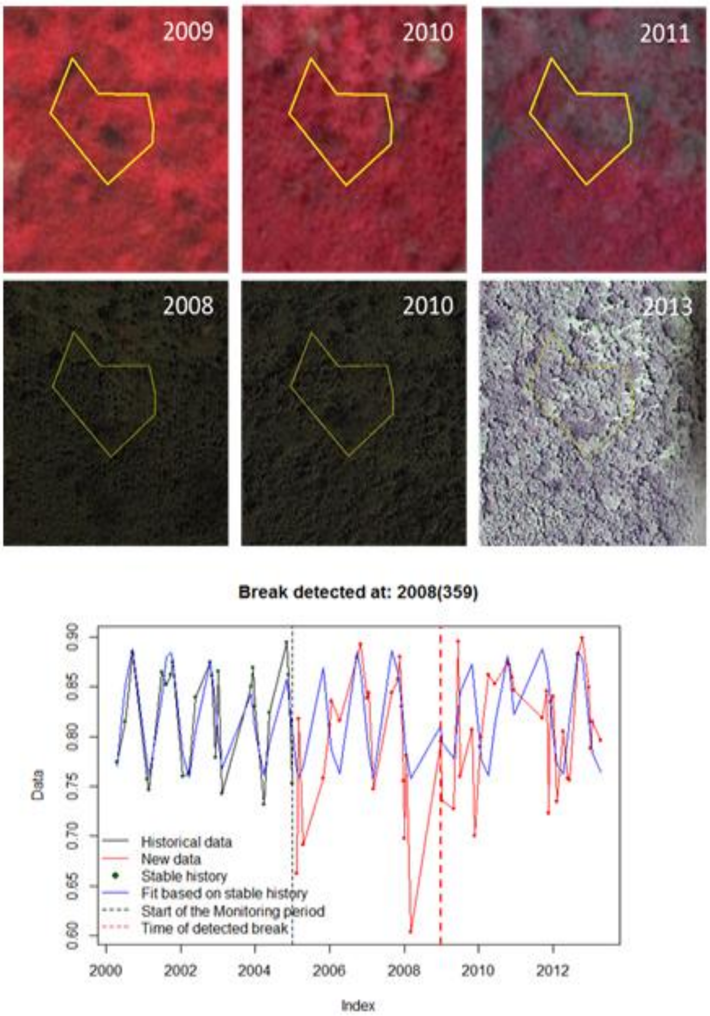
Appendix A : Temporal Lag : it is the difference of data or time of disturbance between the local experts and the reference data sets on a single forest disturbance polygon or area. Negative value of temporal lag indicates that a local expert time estimation is presented before the reference satellite images. And positive value indicates that the delay of the local experts date of time of disturbance from the reference data sets. BFAST magnitude shows the magnitude of changes on the trend of time series analysis. A small demonstration is given below in Appendix B to show how the date of disturbances are detected in different datasets and computed the temporal lag with the local experts data.

	Data or time of forest disturbance from different data Source					Temporal Lags			
Id	Landsat (BFAST)	Spot5-Rapid Eye	Google Earth	Local experts	Validation Data	Landsat Vs Local expert	Spot5_Rapid eye Vs Local expert	Local Expert Vs Validation data	BFAST-Magnitude
1	2005	2012	NA	2007	2013	2	-5	-6	-0.01668377
2	2009	2011	NA	2011	2011	3	0	0	-0.02204221
3	2007	2007	NA	2013	2012	6	6	1	0.007535383
4	2012	2012	NA	2013	2012	NA	1	1	-0.03525893
5	NA	NA	NA	2012	2012	NA	NA	0	0.001605784
6	NA	2011	NA	2011	2011	NA	0	0	-0.00295564
7	2007	2011	2002	2013	2013	6	2	0	-0.1058166
8	NA	NA	NA	2013	2011	NA	NA	2	0.01590797
9	2007	2011	NA	2012	2012	5	1	0	0.001314663
10	NA	NA	NA	NA	2013	NA	NA	NA	0.03680119
11	2007	NA	NA	2012	2012	5	NA	0	-0.08690124
12	NA	2011	NA	2005	NA	NA	-6	NA	-0.00129532
13	NA	2009	NA	2005	2013	NA	-4	-8	-0.00289283
14	2008	2012	NA	2008	2012	0	-4	-4	-0.00809237
15	2008	NA	NA	NA	NA	NA	NA	NA	-0.0757005
16	2006	NA	NA	NA	NA	NA	NA	NA	0.01142609
17	2005	NA	NA	NA	2011	NA	NA	NA	-0.01103441
18	2007	NA	NA	2003	NA	-3	NA	NA	0.04214986

19	2008	NA	NA	NA	2005	NA	NA	NA	0.01399232
20	2008	NA	NA	NA	2013	NA	NA	NA	-0.02792098
21	2008	2007	2002	2006	NA	-2	-1	-7	-0.00414800
22	NA	2012	NA	2013	2012	NA	1	-1	0.01515336
23	2007	2009	NA	2012	2013	5	4	0	0.02830788
24	2008	2011	2010	2010	2010	2	-1	0	-0.00244317
25	2009	2011	2012	2012	2013	3	1	1	-0.04413491
26	2008	2009	2008	2013	2007	4	4	NA	-0.0866611
27	2008	2007	NA	2008	2008	0	1	6	-0.05810687
28	NA	2011	NA	2013	2011	NA	2	2	-0.00380098
29	2009	2011	NA	2011	2011	3	0	0	-0.02929115
30	2008	2012	NA	2010	2013	NA	NA	NA	-0.02119273
31	2011	2011	NA	2012	2012	1	1	0	0.01398109
32	2007	2009	NA	2011	2011	4	2	0	0.02848573
33	2005	2006	NA	2013	2006	8	7	7	-0.0267174
34	2011	2012	NA	2011	2012	0	-1	1	-0.00243967
35	2012	2012	NA	2012	2013	0	0	1	0.0210669
36	2009	2011	2008	2011	NA	NA	NA	NA	-0.06791404
37	2008	2011	NA	2011	2013	3	0	2	-0.02176612
38	NA	NA	NA	2013	2013	NA	0	0	0.02507575

NA – Not Available   No disturbances

Appendix B : A demonstration to show how to calculated the temporal lags between the local experts and the reference data sets. Here, in this example we used three remote sensing reference data sets mainly Spot 5-Rapid Eye in the first row, Google Earth imagery in the second row, BFAST result from Landsat data in the bottom and local expert data in the table (right side column). The temporal lag(year) is calculated between the data sets according the time difference in detected the forest disturbances. In order to reduce errors, a reference data sets, which haven't an image acquired in the same year with the local experts are avoided.



Local Experts Data	
Attributes	Values
Location	Medabo
Date of data collection	2013
Distance to road	3 km
Distance to near village	2 km
Distance to core forest	0 km
Forest type	Natural
Date of disturbance	2010
Evidence of disturbance	Selective logging and Coffee plantation
Drivers of forest disturbance	Selective logging
Current Land use	Coffee investment
Area of disturbances	2 hectare