Remote Sensing supporting national forest inventories NFA

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IN THIS CHAPTER YOU WILL LEARN ABOUT:

- An outline of Remote sensing methods for forest inventories
- Highlights of the frame conditions for the use of remote sensing in NFAs
- An outlook on new sensors such as Lidar and Radar
- Examples for practicable applications

Introduction

This chapter deals with the integration of remote sensing data for national forest inventories. It will give a basic understanding of how remote sensing can be integrated in national forest inventories (NFA) and what aspects are important. It will give an overview of different remote sensing systems, data types, the advantages and disadvantages as well as future developments.

Remote sensing data have been used in forest inventories for a long time. In fact, forestry people were the first, after the military sector, to use remote sensing data to a larger extent in order to support their inventory tasks. If we talk about remote sensing, all air-borne and space-borne instruments for earth observation are included, from analogue aerial photography to space-borne digital instruments like synthetic aperture radar (SAR) and opto-electronical systems. Not included in this definition are satellite positioning or navigation systems and terrestrial remote sensing systems like terrestrial photogrammetry or terrestrial laser scanning. Navigation or positioning systems, as well as terrestrial remote sensing systems, are of increasing importance for sampling and sample based field measurements, therefore they cannot be neglected when the use of remote sensing is described for NFAs. However, this is not what most people refer to when talking about remote sensing, and it will not be included in this chapter. .

Background and Objective

The use of remote sensing data in NFAs is always complementary to sample based field measurements and should be integrated in a sample based terrestrial design. The reasons for integrating remote sensing data into NFAs are manifold. The main arguments for the integration of remote sensing data are:

- Full coverage of the area in relatively short time
- Less costs due to reduced sampling intensity (some satellite data are freely available)

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- Visual documentation of the situation and the changes
- Generation of map data
- Accessibility of information from terrestrial inaccessible or "difficult to access" areas
- Increase of national capacity in mapping, monitoring and reporting
- More harmonized information assessment for the whole country
- Retrospective assessment of changes (the changing situation from the past until today)

The listed advantages have promoted the integration of remote sensing information into NFAs. However, there are also a number of disadvantages which till today prevent a comprehensive integration of remote sensing data into NFAs and forest inventories in general. In Europe aerial photography is widely used for NFAs. In countries outside Europe the integration of satellite data is more common if NFAs are carried out. This is due to the often very large area to be covered and the high logistic barriers for airborne data. The main obstacles to integrate especially space-borne remote sensing data are:

- Data availability (can I get the data I need and where can I get it?)
- Weather conditions
- Long term perspective for space-borne systems (Are the data over long time period available?)
- Problems of clear assignment of areas with-without trees to forest according to the respective definitions
- Additional costs if existing terrestrial sampling design is retained
- Limitations to derive the traditional set of forest parameter from airborne and space borne data
- Missing technical capacity
- Flight permission for air-borne data take.

Considering the technological developments and the increasing number of earth observation satellites in orbit within the last 20 years, it can be assumed that remote sensing data beyond aerial photography will have increasing relevance for NFAs. There are already a number of countries in which space-borne remote sensing data are an integrated part in their NFAs. Also the Forest Resource Assessment (FRA) 2010 by the Food and Agriculture Organisation (FAO) has now a fully integrated remote sensing component. After testing the integration of space-borne remote sensing in former FRAs with focus on tropical forests, they state: "*Satellite data enable consistent information to be collected globally, which can be analysed in the same way for different points in time to derive better estimates of change. Remote sensing does not replace the need for good field data but combining both provides better results than either method alone*" (Global Forest Resource Assessment 2010). This has led to a global integration of space-borne data for forest area and forest area change estimations. A driver for the use of information from satellite or airborne remote sensing data is also the accessibility of remote sensing images through google maps. This triggers the use of remote sensing based information even though google maps only allow the use of images for visual interpretation but no image processing for automatic information production (e.g. automatic classification of forest types). Objective of this chapter is now to give information on the integration of remote sensing data in NFAs, what are the considerations needed for a general set up, what kind of data are available and what methods can be used.

Consideration for a general set up to integrate remote sensing data into NFAs.

Before any decision can be taken on how to integrate remote sensing data (and what kind) into NFAs, it is important to identify the information which shall be derived from remote sensing data and what kind of product and information shall be delivered at the end. The identification of the forest parameters requested from the data and the identified output at the end, largely define the inventory design and the data needed. If forest parameters shall be derived based on multi-phase inventories, then the sample design has to be carefully considered. For example, if a sampling with remote sensing data (e.g. very high resolution satellite data) is carried out and the remote sensing based information needs to be calibrated with terrestrial sampling data, then there needs to be an overlay between terrestrial plots and satellite samples. In all forest inventories using remote sensing data the main information derived from these data are the forest area and forest area change estimations. This seems simple and it has been carried out many times. But, already, this rather simple request includes a number of considerations and decisions. The first decision is related to the product at the end. Is a wall to wall mapping required, a sample based approach or a combination of both? In many cases a combined approach is the best solution, having a full coverage with either medium or high resolution data, like the Modis data with 0.5 to 1 km spatial resolution as used in the FRA 2010 or even high resolution data like Landsat TM as integrated in the NFA for Finland. The choice between using medium or high resolution data depends mainly on the area which needs to be covered, the budget available, the needed scale and if any other information shall be extracted in addition. Based on full coverage data, a forest mask or a landuse map combined with a forest mask is produced.

Table 1

Suitability of selected satellite sensors for forest Monitoring (source: Ridder 2007)

Image type	Free / low cost	No copy right	Optimised for vegetation	Length of repeat cycle	Available time range	Future sensor continuation
Optical, 5 to 50 m pixel resolution						
ASTER	+	-	+	- (16 days)	2000 onwards	unclear
CBERS CCD + IR-MSS	?	?	+	- (26 days)	2000 onwards	expected
DMC	-	-	+	+ (near daily)	2005 onwards	unclear
IRS LISS	-	-	+	- (5-24 days)	1997 onwards	expected
Landsat MSS	+	+	+	- (16 days)	1972-1984	N/A
Landsat TM & ETM+	+	+	+	- (16 days)	1984 onwards, since 05/2003 SLC off	LDCM
RapidEye	-	-	+	+ (daily)	2007	unclear
SPOT HRV	-	-	+	- (26 days)	?	expected
Optical, 150 to 1000 m pixel resolution						
CBERS WFI	?	?	+	+ (3-5 days)	2000 onwards	expected
IRS WIFS	-	-	+	- (24 days)	1997 onwards	expected
MERIS	?	?	+	+ (daily)	2000 onwards	expected
MODIS	+	+	+	+ (daily)	2000 onwards	VIIRS
SPOT VEGETATION	+	-	+	+ (daily)	1998 onwards	Vegetation 2
SAR						
ERS	-	-	-			
JERS	+	-	+			
RADARSAT	-	-	-			
ENVISAT	-	-	-			
TerraSAR-X	-	-	+/-		To be launched in 2007	unclear
ALOS PALSAR	-	-	+		2006 onwards	unclear

Even though Modis and Landsat TM data are often used for full coverage mapping there are a number of other satellites which are feasible for this task. One main driver for the selection of sensor type is the life span of the satellite sensor. Table 1 shows a selection of satellite sensors for forest monitoring as described in the FRA Working paper 141 (Ridder 2007).

More and updated information can be extracted from the EO portal (https://directory.eoportal.org/index.php). The portal also provides information on upcoming satellite missions. One good example is the Sentinel 2 mission by ESA, which will provide wide swath high resolution twin satellites. This mission is planned for a long life span. Brazil and China are also expected to provide long life satellites, in addition to India and the U.S.. Another very important aspect, when planning the set up for the integration of remote sensing into NFAs, is the repetition rate of the sensor type. This is especially important for countries with unfavourable weather conditions. Before the decision for a sensor type is taken, calculations or approximations on the probability of getting cloud free scenes, should be carried out or a catalogue with existing data should be analysed because this can be a very critical issue if the data are needed for a certain time period. Fig. 1 gives an example for the probability of mean cloud fraction in Landsat ETM acquisitions (Yu and Roy 2007).

In the future, especially those sensor types will be used successfully in NFAs: those which provide fairly high repetition rates as it is planned with Sentinel 2. The Sentinel 2 will provide a revisit every 5 days. According to a study (source unknown) based on Landsat TM data, simulating a 5,5 day revisit, the chances, globally, for cloud free scenes would increase on average by around 30% if compared to the 16 days revisit of today. Then, only a few tropical and sub-boreal forested regions will still have problems to acquire cloud free scenes within a reasonable time with a high revisit of 5 days. For those areas, alternatives like SAR sensors or optical sensors with daily repetition are needed. Also, the time of the year has an influence on the probability to get a cloud free scene. In general, during the summer and winter period, in many regions, it is more difficult to get cloud free scenes than in spring or autumn.

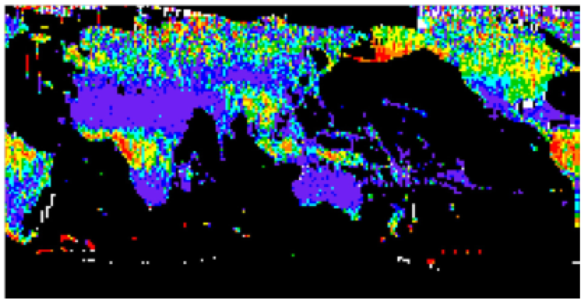
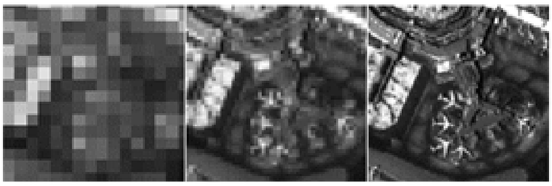


Fig. 1: Mean cloud fraction in ETM acquisitions for each global land scenes in 2002 0<purple<0,2, 0,2=<dark blue<0,3, 0,3=<light blue<0,4, 0,4=<green<0,5, 0,5=<yellow<0,6, 0,6=<orange<0,7, 0,7=<red<1.0. (source: Yu and Roy 2007)

Besides space-borne remote sensing, also airborne remote sensing can be used. The application of airborne data in NFAs is mainly a question of costs and practicability. In many countries the integration of airborne data fails due to the limitations to get a flight permission. Secondly, due to the size of the country, a full coverage by airborne systems is not possible and even in the frame of a multi-phase inventory, a sampling with airborne data is a logistic challenge.

After having considered the aforementioned general conditions, the set of eligible sensors has to be analysed according to four major characteristics in order to fit best the information and mapping requirements. The selection of the eligible sensors can be best done together with companies which sell data and the requested information products. However it is always of advantage if the customer is well aware about the quality of different satellite data because this provides an idea of what information will be possible. The major components which define the later image quality are the following:

- Spatial resolution defines the ability of a sensor to identify the smallest size detail of a pattern on an image

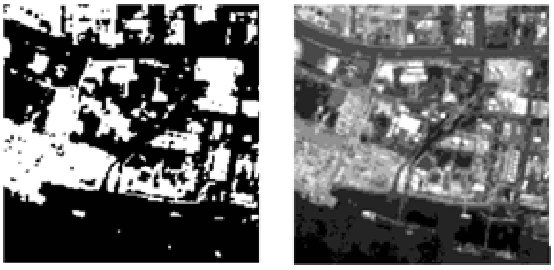


pixel size 30 m pixel size 10 m pixel size 3 m

Source: Earth watch

Fig. 2: Examples of images with different pixel size

- Radiometric resolution defines the ability to detect differences in the reflected energy. For example, if there are two paved flat areas, which differ only slightly in grey colour then in the black and white image of the sensor with low radiometric resolution there is no difference between the two areas while in the black and white image of the sensor with high radiometric resolution there will be a difference between the two areas.



1 bit greylevel image 8 bit greylevel image

Fig. 3: 1 bit and 8 bit radiometric resolution (source: unknown) - Radiometric resolution smaller than 8 bit is considered low radiometric resolution, 8 bit is medium radiometric resolution and 12 bit and more is considered high radiometric resolution

- Spectral resolution is the sensitivity of a sensor to respond to a specific frequency range: how many different spectral regions the reflected energy can be measured e.g. for a colour composit the sensor has to have the ability to measure the reflected energy in at least 3 different spectral regions (channels).

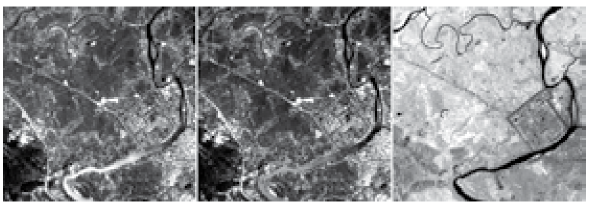


Fig. 4: The different spectral channels of Landsat TM (B2 to B4 left to right)

- Temporal resolution defines the repetition rate of the satellite that means in which time sequence the satellite will have the potential possibility to make a data take over the same area e.g. daily, weekly, monthly.

Optical sensor systems

The integration of remote sensing based data into NFAs is mostly related to optical systems. There is a long tradition of aerial photography as a supporting information source in NFAs as well as in commercial inventories. According to the aforementioned major characteristics, aerial photographs have a very high spatial resolution, a high radiometric resolution and the spectral sensitivity is over the visible to the near infrared range of the electromagnetic spectrum (400 nm to 1100 nm). While in the past analogue systems with film material were used, today more and more digital airborne cameras with normally 4 spectral bands, 3 in the visible and 1 in the near infrared are used. A temporal resolution is not applicable for aerial photographs because the flight time is more or less freely selectable. The probability to get cloud free data from aerial photography is therefore higher than from satellite based optical systems due to the high flexibility of date take. Especially within Europe aerial photography has still a prominent role within forest inventories. In a number of countries the forest non-forest decision and the change in forest area is based on aerial photographs. The reasons for the intensive use of aerial photographs in Europe are probably the long tradition in use of aerial photographs, the high spatial resolution aerial photographs provide, the often strong interrelation between the survey institutes which produce the aerial photographs and forest administration, the relative high costs for very high resolution satellite data (very high resolution satellite data can still not compete with the costs of aerial photographs) and the higher probability to get cloud free data for the envisaged area within a certain time. Other factors which facilitate the use of aerial photography in Europe are the relative easy to get flight permission and the relatively smaller mapping units compared to other areas like U.S and South America. The new generation of digital aerial photography will probably further advance the complementary use of aerial photographs along with terrestrial measurements, due to better radiometric and spectral characteristics and the increased possibilities in data processing. Investigations by Hoffmann (2010) showed that, based on digital infrared aerial photographs, it was possible to assess important forest parameters, like major tree types, gaps and damages. The potential information from stereo aerial photographs, tree height, is normally not used to derive further forest properties, like wood volume or above ground biomass estimations. In a number of countries aerial photographs are the only type of remote sensing data used within a NFA. One use of aerial photographs within NFAs is to reduce the number of terrestrial samples plots without loss of information and accuracy (e.g. Switzerland).

Often, outside of Europe but also in some countries within Europe, optical satellite data are used as complementary data source for NFAs. In general not very high resolution satellite data are used but high resolution satellites like Landsat TM. By far the most used satellites in NFAs are the Landsat satellites. This is mainly due to the low or no data costs and the long life span of the Landsat series. In general satellite data are used for wall to wall mapping, like in the case of the Finnish inventory, but also for sample based mapping. If we refer to the four sensor characteristics which have to be analysed before deciding which sensor type should be used, the most problematic requirement today is the temporal resolution of the available satellites, while spatial, radiometric and spectral resolution are for a number of satellites (e.g. Landsat TM, Spot, IRS) suitable for forest inventories. Temporal resolution is critical especially for forest inventories because the forest is often located in areas with relatively high cloud coverage. An internal study by the DLR, Germany showed that, on average, it takes 5 years to fully cover Germany with cloud free Landsat TM scenes. Therefore a major consideration is to ensure a sufficient temporal resolution which will improve the data availability. Secondly, costs will have a strong influence on the use of remote sensing data in NFAs. The higher the resolution the more difficult it is to get a full coverage of a large area and the more costly it will be. Fig. 5 shows the coverage of different sensors scenes.

A wall to wall mapping with very high resolution satellites is not feasible in a NFA, this is due to the costs and the difficulties to get a full coverage within reasonable time. A wall to wall mapping however is useful for any kind of stratification and for the forest-non-forest decision (Öhmichen 2007). Investigations by McRoberts (2002) and Dees and Koch (1997) show that a stratification of the forest area based on optical satellite data improves either the accuracy of the estimates or allows a reduction of the sample plots without loss of accuracy. If a stratification is applied there are two approaches: pre-stratification or post-stratification. While pre-stratification will have an influence on the sample plot design, post-stratification allows keeping the existing sample plot design.

In many cases the integration of remote sensing data is based on a multi-phase approach. In this case, for example, forest-non-forest classification is based on medium resolution data, while in a second phase high

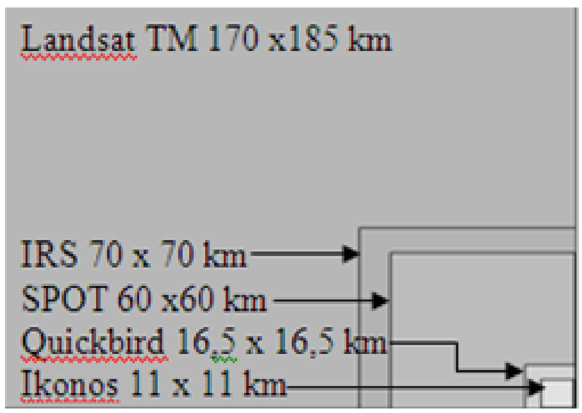
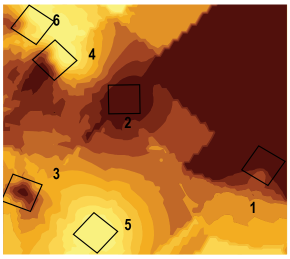


Fig. 5: The relation of the coverage areas from different sensors

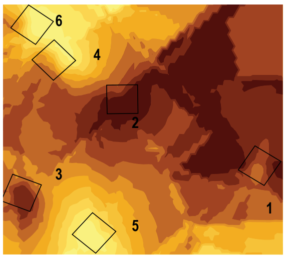
resolution satellite data, very high resolution satellite data or aerial photographs are sampled. For the sampling, the data used vary from high resolution to very high resolution satellite data or aerial photography. The selection of data type is mainly dependent on the forest parameters which shall be derived from the remote sensing data. If forest condition, tree species or forest structure shall be mapped, then aerial photography or satellite data with very high spatial, spectral and radiometric resolution are needed.

A number of investigations have been carried out to estimate wood volume and above ground biomass from optical data based regressions. There are correlations between the reflected signal and wood volume as well as above ground biomass in the near-infrared, the short-wave infrared and for some indices. However it has to be mentioned that the variance is very high and the higher the wood volume and above ground biomass of a forest the lower is the correlation. Nevertheless, especially for the modelling of CO2 sequestration, remote sensing data will have high importance in future because remote sensing is the only tool which can provide information on the forest condition and forest area on a global level. The first outlines on how optical satellite data can be used for the modelling of CO2 binding is presented in the GOFC-Gold source book (2009). In the future, biodiversity information will also gain importance in NFAs. If biodiversity is to be mapped, two different biodiversity types need to be considered: structural biodiversity and species diversity. Remote sensing can provide information to both categories at the landscape level. The identification of species in remote sensing data is limited to tree species or forest types. While tree species identification is mostly based on near-infrared aerial photographs, the identification of forest types can be carried out with very high or high resolution multi-spectral satellite data. However it should be noted that the identification is limited whether using aerial photographs or satellite data. Besides spectral similarity of some tree species, the limitations are originated by the age of the trees (a tree can change its spectral properties drastically over age), the mixture pattern of tree species, and the condition of trees. This is the reason why in tropical and sub-tropical areas, with a tight mixture of a high number of tree species, forest type identification is often not possible. In addition, the exposition of the forest areas can vary, thus increasing the problem of species or forest type identification based on reflectance values. The problem of reflectance differences due to different exposition towards the sun cannot be fully removed by any correction algorithm. Nevertheless, with good processing, reasonable results can be achieved. With the availability of hyperspectral data, investigations show that forest type and species recognition can be improved. In general, the structural diversity is better accessible by remote sensing data. Especially the horizontal structural diversity can be mapped quite well and even better than with terrestrial measurements. The quality of the result is mainly influenced by the availability of a good match between the spatial resolution and the requested mapping scale for the structures (Fig. 6).

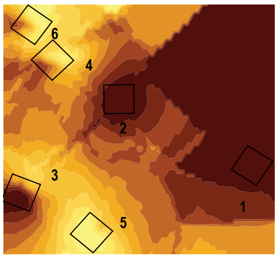
Fig. 6: Segmentation of forest area based on IRS-1D and Landsat TM fused image (source: Ivits et al. 2004)



Ordinary Kriging surface calculated from observed values



Ordinary Kriging surface of values predicted from grey values



Ordinary Kriging surface of values predicted from patch indices

Fig. 7: Segmentation of forest area based on IRS-1D and Landsat TM fused image (source: Ivits et al. 2004)

Investigations at FeLis[1] showed that, based on structural and forest type information extracted from Landsat TM and IRS-1D data, it is possible to model habitat structures for bird species. Based on grey-values and grey value derived indices from Landsat TM and IRS-1D, high significance was showed by a goodness-of-fit test (Hosmer and Lemeshow 2000) for a corresponding final logistic model predicting the absence and presence of certain bird species (C=4.2610, P > Chi-Sq= 0.8328) (Herrera 2003). This indicates that for certain bird species the presence and absence is strongly correlated with the grey-value derived co-variables which are included in the model. The c statistic indicates that 92.9% of the probability of the bird species occurrence is determined by the listed co-variables.

Investigations by Ivits et al. (2004) also showed that patch indices and grey values achieved similar results in predicting the presence of certain bird species. Logistic regression denoted strong predictive power of the remote sensing variables (Fig. 7.). It seems that remote sensing indices can be very useful indicators of bird species diversity when bird species are handled separately while it is less effective in the case groups of species.

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SAR and Laser scanner data

SAR Data

While it can be assumed that optical remote sensing data will be of increasing importance for NFAs in future, the application of SAR data will probably stay limited. This is due to the high complexity of radar data processing and the limitations they have in mountainous areas. The main advantage of radar data is their transmission through clouds which makes the data fairly weather independent. With L-band data the forest non-forest decision and therefore the changes in forest cover can be assessed quite well (Häme et al. 2009), even with automatic classification procedures. Also in C-band and X-band data, image interpretation of forest areas is possible (Fig. 8).

Nevertheless there are strong limitations in mountainous areas due to the radiometrical and geometrical problems which occur in the data. Even though there are a number of correction algorithms, the radar shadow and the differences in backscatter intensity due to incidence angle cannot fully be corrected. This limits the use of radar data in NFAs even for the forest non-forest decision.

Fig. 8: Colour-coded TerraSAR image north of Munich. Data take 26. June und 7. July 2007, 5:26 UTC, resolution: 3 m, mode: Stripmap, polarisation: VV und HH (source: DLR, Germany

The extraction of forests parameters from radar data is difficult and results are not consistent. Algorithms and models exist but they are more a matter of research and it is not practical to integrate them into NFAs. A lot of work has been carried out on the use of radar data for above ground biomass assessment (Koch 2010) however the studies are not based on robust tests and only apply to the specific forest and data take situation. The assessment of above ground biomass with radar data is restricted by the saturation which is reached for forest areas with high wood volume or high above ground biomass. Nevertheless in forest areas with low above ground biomass, like in boreal or sub-boreal regions, reliable measurements are possible. In general, radar data can be quite valid for integration into NFAs if certain environmental conditions are fulfilled: flat to hilly area and relatively low above ground biomass and wood volume. There are some new investigations which indicate that the saturation problem can be minimized, however this is still solely a matter of research. Nga (2010) writes that L-Band and P-band data with cross polarization are most sensitive to above ground biomass, like it was stated by others before (LeToan 1992, Kurvonen 1999). Especially cross polarized P-band could substantially contribute to the modelling of above ground biomass (Henderson and Lewis 1998). This is due to the fact that cross-polarized backscattering in the L- and P-band is related to volume scattering which is correlated with above ground biomass. The problem of saturation can be reduced with longer wavelength but according to the publication by Nga (2010) it remains a problem for forests where the above ground biomass is over 200-250 Mg/ha. The identification of tree species or forest types is, to my best knowledge, not possible. Even the separation of broadleaf and conifer forests is not very reliable. Taking into consideration the existing limitations and the complexity of radar data processing as well as the lack of long earth observation radar satellite for L- and P-band, the integration of radar data into NFAs seems until today difficult. The use of airborne systems is possible however quite expensive and not enough commercial providers offer these kind of data in order to integrate airborne radar data into NFAs.

Laser data

The use of laser data within forest inventories has boosted within the last years. Most projects are still in research but could prove to be of high value for practical applications in forest inventories (Næsset, E., 2004, McRoberts 2010) . The use of airborne laser (ALS) data for forest applications is probably the most innovative development in remote sensing for forest inventories within the last 10 years. The enormous potential of ALS data is primarily based on the possibility to model the forest surface and the forest ground from one data set. In addition it is possible to assess vertical forest structures. The extraction of accurate height information over forests allows the modelling of several important forest parameters. Height is nearly adequate to DBH as input variable for modelling important forest parameters like wood volume and above ground biomass. DBH and DBH distribution, which are important information for forest managers can also be assessed from height. There are two approaches to model forest parameters, the first is an area-based approach which can work with low density data (Fig 9), the second is the single tree based approach which needs high density data with 8 to 10 points per m^2 to achieve good results. Many investigations have been carried out on this topic and Hyyppä et al. 2009 gives a comprehensive overview on the status of ALS data in forest inventories.

Area based approaches can be performed as regression analysis, kNN analysis or yield table methods. This is described in detail by Straub et al. 2009. Investigations by Latifi et al. 2010 demonstrate that the use of laser derived information is not only superior to Landsat TM data but also to aerial photographs for important forest parameters such as wood volume and above ground biomass (Tab 2).

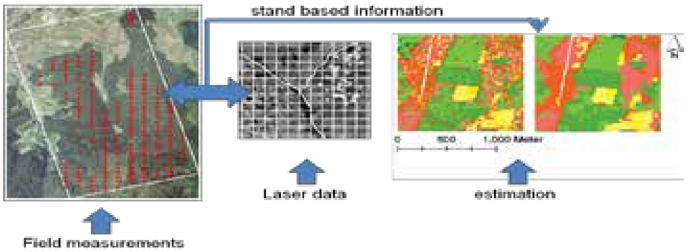

Fig. 9: Schema for an area based approach to estimate forest parameter

Besides good estimations for wood volume and above ground biomass, many other parameters which are of increasing relevance in NFAs, like crown density or forest structure parameters as indicators for forest biodiversity, can be estimated with high quality using the area based approach from laser data. What is more difficult up to now is the identification of tree species or forest types. While it is possible to separate with high quality broadleaf from conifers using different methods, the further identification of tree species or forest types is not very practicable with laser data. Even though there are some successful investigations (Heinzel and Koch 2011, Vauhkonen et al. 2010, Hollaus et al. 2009, Höfle et al. 2008) using geometrical as well as physical information from airborne laser data for tree identification, the results are not in a state for operational application in a NFA. Within the last years the single tree approach has gained more and more interest for forest inventories. Investigations showed that the integration of sample based single tree information is especially needed in mature stands for better management as well as harvest and nature protection planning. The single tree delineation is a challenge and the quality which can be achieved is dependent on the data quality, the forest types and the algorithms used. A comparison of algorithms in different stand types has been carried out by a group of researchers in the frame of the WoodWisdom project (Fig. 10) (Vauhkonen et al. 2010). While the performance of different algorithms was similar, with not much difference, the main problem was the kind of stand type. In coniferous stands the detection rate was much better then in broadleaf multilayer stands.

Laser data integration into NFAs is only possible in the frame of a multi-phase inventory on the basis of sample plots, due to the fact that laser are normally operated from airborne platforms which cannot be applied for wall to wall mapping covering large forest areas. The only satellite based system IceSat/Glas is out of work and the data were only useable for research purpose. A planned satellite based Lidar system will only be available in a few years. This limits the application of laser data mapping within NFAs.. On the other hand, in the frame of a multi-phase inventory, laser data can give very valuable information on many forest parameters assessed during NFAs. The use of sample based Lidar data will reduce the

Tab. 2

Plot level RMSE, RMSE% and Bias% for CIR Images, Landast TM and LiDar data for standing timber volume and above ground biomass across different imputation methods (source: Latifi et al 2010)

	CIR image			TM image			LiDAR data		
	RMSE	RMSE%	Bias%	RMSE	RMSE%	Bias%	RMSE	RMSE%	Bias%
Euclidean distance									
Volume	154.31	58.65	1.93	142.73	54.25	−2.91	119.61	45.46	0.75
Biomass	95.49	56.92	1.79	88.43	52.71	−2.80	74.46	44.38	0.30
Mahalanobis distance									
Volume	145.76	55.40	2.65	158.74	60.33	1.68	127.55	48.48	2.42
Biomass	89.15	53.14	2.28	97.37	58.04	1.71	79.60	47.45	2.56
MSN									
Volume	145.54	55.32	0.57	148.40	56.4	−0.33	98.411	37.40	0.72
Biomass	92.55	55.16	2.09	90.68	54.05	−3.39	61.59	36.71	1.94
RF									
Volume	109.21	41.51	−1.84	117.12	44.51	−1.48	54.438	23.97	−1.97
Biomass	65.01	38.75	−3.16	69.90	41.66	−3.31	37.32	22.24	−2.44

number of terrestrial sample plots and/or the accuracy. The information inherent in laser data is compared to other remote sensing data probably the highest in respect to a number of forest parameters. However the data are still not standard and are more costly than aerial photography, which is a serious concern for the integration of Lidar data into NFAs today. In many countries the application of Lidar is also quite difficult due to missing commercial providers and flight restrictions. In addition, a major drawback is the poor information on tree species. More research is still needed for a multi-sensoral approach on one platform like laser combined systems with multi-spectral scanner or a multi-wavelength lidar system working at three different wavelength. For further advances, better exploitation of the full-wave and physical information, like intensity, still needs to be investigated.

Information processing

The exploitation of information from remote sensing data can be quite different. In many applications the visual interpretation of images is most practical way to extract the needed information. Within the FRA 2010 as well as the REDD initiative, image interpretation is used for the identification of the forest area, the area change as well as the degradation of forests. However interpretation is cost intensive and subjective. The results depend largely on the training of the interpreters and are difficult to compare. The subjectivity already starts with the classification of forest area, because the delineation of forest boundary is not always obvious to the interpreter. However it has to be taken into consideration that also a terrestrial assessment is in many cases subjective.

Mainly due to efficiency reasons and to a better standardization of the process machine learning algorithms for classification are preferred. The results might not be more correct than interpretation but they are transparent. A number of different classifiers are well known. **Minimum distance, Maximum Likelihood and Artificial Neural Network** are the classifiers which are used since many years. The simplest method is the Minimum Distance which, based on the mean of the training classes, calculates the shortest spectral vector distances in the multi-dimensional space. The Maximum Likelihood, based on the mean vectors and co-variances of the training classes, calculates the statistical (Bayesian) probability that a pixel belongs to a class. For this a Gaussian distribution is assumed and equiprobability for each class is formed (NASA 2010). Especially the assumption of the Gaussian distribution of the grey values does often not meet reality.

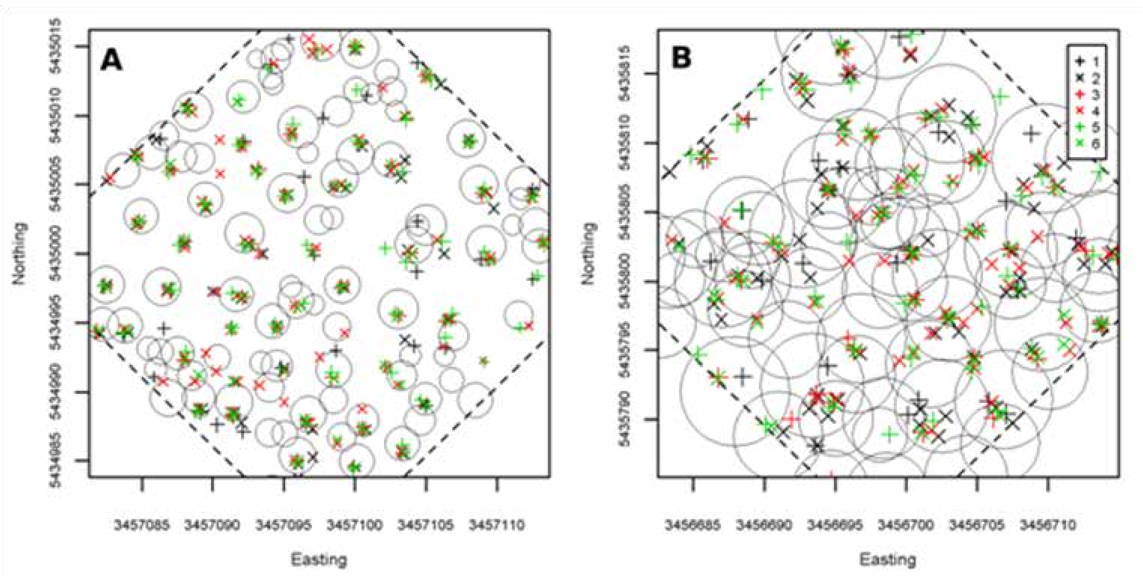

Fig. 10: A- Germany coniferous and B- Germany broadleaf multilayer stand. Numbers 1 to 6 are the different algorithms.

Artificial Neural Networks are not so much in practical use, mainly due to the fact that this classifier is computing intensive and did not yet prove its superiority. Artificial neural network algorithms image the neural structure of the brain. They start with a set of input data and learn by comparing the classifications with the known actual classification. The results are fed back into the network, and used to modify the network algorithm for as many iterations as needed (Zhang et al 2000).

In the nineties, **the object oriented classification** algorithms (Lillesand et al. 2008) gained more and more interest. Here the classification is a two step approach. In the first step a segmentation (grouping together adjacent pixels into segments or regions according to similarity criteria) is carried out mainly based on reflectance properties (colour), texture and shape. Pattern and context can also be taken into consideration. This is carried out as a hierarchical classification and therefore each class can be described by its optimal scale. In the second step the segments are classified. In many cases the **Nearest Neighbour** classifier is used (McRoberts 2011), which is similar to the Minimum Distance classifier. While the Nearest Neighbor classifier is based on multi-dimensional spectral distances another option is the **Fuzzy classifier**. This classifier tries to take into consideration the problem of mixed pixels. This means for each pixel a membership function is calculated and the probability to belong to one or the other class is provided (Nedeljkovic 2004). The most prominent software for object oriented classification today is eCognition. Relatively new are the **Support Vector Machine** and the **Random Forest** classifiers. Both classifiers are in the focus of the science community today. With both classifiers good classification results are achieved in land-use and forest classifications. Support vector machines (SVMs) proved to handle high feature spaces and complex class discriminations better than other methods (Heinzel et al. 2010, Mountrakis et al. 2011). The SVM classification is a supervised non-parametric statistical learning technique which does not require an assumption of the underlying data distribution. This is the major advantage of this classifier. The SVM is always related to a two class separation in a multi-dimensional feature space. Multi class separations are possible by breaking them down into two class problems which are combined in certain ways. The SVM classifier aims to find by an iterative way a hyperplane in which the misclassification is minimized using the training examples. The **Random Forest** classification is based on many individual decision trees. It is a supervised learning algorithm which can handle a large number of attributes and runs efficiently on large datasets. Independent of the number of input variables and runs the classifier is not overfitting. It has produced high accuracies in many classifications (Klassen and Paturi 2010). Latifi et al. 2010 also found that Random Forest classifier performs better than the SVM classification for classification of forest attributes. The advantage of the classifier is that an evaluation of the classifications is performed during the processing. The Random Forest classifier takes “bootstraps” which are samples of the training data set. Parallel classification trees are generated and at each node a random sample of variables is selected. The best split is carried out and the tree grows to the largest extent possible. The tree with the lowest error rate is then selected as the strongest classifier.

Besides the classifiers presented above the **k Nearest Neighbour** (kNN) non-parametric estimator is a very efficient method to use remote sensing data in combination with sample plots in order to get full coverage information. The kNN method is used in the NFA in Finland with good performance (Tomppo 2002). The method is based on the regression between spectral characteristics of image pixels over areas with field measurements and image pixels with no field information. Based on Mahalnobis or Euclidean distance measures of k numbers of Nearest Neighbours the pixels with no field information will get copied the field information of those pixels which have an underlying field information and match best. In this way the information from the field measurements is transferred to the areas with no field information. In the field of forestry a large number of investigations with different kind of sensors have been carried out with the kNN method. The kNN method has proved its usefulness however the type of sensor data and the forest type will have large influence on the results (Latifi et al. 2011).

Concluding remarks

The author does not claim to give with this short overview a complete picture on the use of remote sensing in national forest inventories. The intention was to provide a condensed overview on important aspects according to own experience. The author has not provided any information on sampling design because this is covered by other authors which have more specific experience in this field. For a deeper examination of the remote sensing topic the continuing literature is recommended.

Glossary

ALS	airborne laser scanner
BHD	breast height diameter
CIR	colour infrared
ESA	European Space Agency
FAO	Food and Agriculture Organisation
FRA	Forest Ressource Assessment
GOFC	
Gold	Global Observation for Forest and Land Cover Dynamics
IRS 1	Indian Remote Sensing Satellite
kNN k	Nearest Neighbor classifier
Landsat	
ETM	Landsat Enhanced Thematic Mapper
Landsat TM	Landsat Thematic Mapper
Modis	Moderate Resolution Imaging Spectroradiometer
NFA	national forest assessment
REDD	Reducing Emissions from Deforestation and Forest Degradation in Developing Countries Programme
RMS	Root Mean Square Error
SAR	Synthetic Aperture Radar
SVM	Support Vector Machine

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