Extending Forest Inventories and Monitoring Programmes Using Remote Sensing: A Review

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Abstract
This paper presents a review of remote sensing technologies that are applied in forestry. It presents an overview of the data sources and applications that are used to map, monitor and estimate forest parameters. In particular, it deals with methods that use data from space borne sensors as well as methods that utilise terrestrial, active remote-sensing methods. The paper also comments on techniques that have already been used in Ireland, but also discusses other methodologies that are relevant to the Irish forest sector, including supporting field based inventories, updating digital map datasets and providing high-resolution forest stand estimates at a range of scales. In addition, the paper presents techniques to monitor land-use, land-use change and forestry (LULUCF) and to upscale field plot measurements with remotely sensed data.

Keywords: *remote sensing, forest monitoring, forest inventory, optical imagery, LiDAR*

Introduction
Field inventory techniques have been employed in forestry to assess and monitor forests at a range of scales, from stand management through to regional and national inventories. These inventories are based on sampling methods - either random, systematic, stratified or cluster sampling. Using the data collected during these inventories, they provide a direct means of inferring forest parameter estimates of forest areas.

Due to the extent of forest resources, forest practitioners have long considered remotely-sensed imagery as a useful source of data to incorporate into their inventory and monitoring practises. Aerial photography has been used since the early 1940s to map the extent of forest resources as well as to derive other stand information, such as species composition and the extraction of tree height using stereo-photos (Lund et al. 1997). Its use, now in digital format, continues to be widespread within national and stand forest inventories; however, in recent years, in some cases their use has been replaced by spaceborne satellite imagery due to its comparatively lower cost per unit area (Tomppo et al. 2008a; McRoberts et al. 2002).

Since the launch of the first Landsat sensor in 1972, the multi-spectral nature of the resulting images has been integrated into regional and large-scale forest monitoring programs (McRoberts and Tomppo 2007). Although the spatial resolution (the individual size of each picture element) is coarser than in aerial photography, the synoptic view, image information from a wider light spectrum and large extent of

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multi-spectral satellite images offers substantial advantages for forest inventories. Over the past four decades the number of Earth observation satellite sensors has increased exponentially, ranging from low resolution to very high spatial resolution imaging sensors. More recently, active sensors, such as RADAR and LiDAR instruments have gained considerable popularity due to their ability to record data independently of light and prevailing weather conditions, whilst producing high resolution information pertaining to the structure of the Earth's surface and, in particular, living vegetation.

The aim of this paper is to provide a comprehensive review of remote sensing research and operational use cases relevant to forest monitoring and forest inventory programmes. It focuses on the use of optical satellite imagery and active remote-sensing data for forest mapping and outlines the principle advantages and limitations of these technologies within forestry applications in Ireland. It concludes with an outlook on future developments in earth observation science and an overview of opportunities that exist for forest monitoring at a range of spatial scales.

Remote Sensing

Remote Sensing can be very loosely defined as a process of collecting information without coming in contact with the object (Lillesand et al. 2008). With respect to Earth observation, it can be considered to relate to the acquisition of imagery of the Earth's surface.

Efforts to acquire aerial imagery began at the start of the 20th Century using cameras mounted on aeroplanes, balloons and kites. These technologies were adapted and refined largely for military reconnaissance purposes during the First and Second World Wars (Campbell 2002). The benefit of this technology was subsequently identified and used by geographers, geologists and land resource managers (Campbell, 2002). It has long been acknowledged that much information relevant to forestry is discernible on a variety of image datasets and, as a result, a myriad of techniques has been developed to classify forest land in terms of forest related variables that can be seen on the imagery (Horler and Ahern, 1986; Varjo 1996; Wynne et al., 2000; McRoberts et al. 2002; Pekkarinen et al. 2009).

The first step to acquire space borne remotely-sensed data was taken by the United States National Aeronautics and Space Administration (NASA) on the 23rd of July 1972 with the successful launch of the Earth Resources Technology Satellite (ERTS-1), which was later renamed Landsat 1. The Landsat program continued and the technology improved as new sensors were launched. This has led to one of the largest and most comprehensive archives of remotely sensed imagery of the Earth, spanning four decades. This archive was recently made publically available free of charge by the United States Geological Survey at http://glovis.usgs.gov. After Landsat, numerous countries began to develop and launch their own sensors (e.g. France with the Systēme Pour l'Observation de la Terre (SPOT) in 1986, India Remote Sensing in 1989/1991, European Space Agency ERS sensor in 1991, the Disaster Monitoring Constellation [DMC] based in England in 2002, and a range of privately owned sensors, for example Ikonos in 1999). As a result, in the 21st century numerous sensors are acquiring imagery of the Earth at a range of spatial and spectral resolutions with varying swath widths. In addition, the development of sensor technology is advancing and improving at a very fast rate with an associated decrease in the image cost per unit area.

Techniques of forest monitoring

Over the last decade there has been an increased need to monitor forests to assess national-level compliance with international conventions and to quantify global public goods, such as protected forest areas and the contribution of forests to carbon sequestration (World Bank 2008). Data emanating from national forest inventory and remote sensing are both objective means of addressing these needs. Both can be precisely overlaid between different time periods within specific geographic areas and can be used for retrospective spatial analysis. However, the spatial scales relating to the estimation of parameters differ substantially when national forest inventories (NFI) data are used in isolation or in conjunction with satellite imagery. In addition, data acquired from satellite sensors tends to be updated at much more regular and consistent intervals.

Numerous studies have demonstrated that remote sensing can substantially improve forest resource assessments with respect to the added value that the data offer to estimate and map forest variables at a range of scales. In addition, they provide an objective source of data, which can be used for repeated and retrospective analysis (Reese et al. 2002; McRoberts 2008; Tomppo et al. 2008a).

Forest inventories, notably NFIs, extend over large areas and the synoptic view of the landscape provided by remote sensing systems is clearly advantageous. In addition, the repeated acquisition and the objective nature in which the images are acquired are considerable benefits, thus complementing sample-based forest inventories. These benefits were identified during the early 1980s and research was initiated to assess the potential of integrating remotely sensed data into forest monitoring programmes (Häme et al. 1987; Tomppo 1991). Remotely sensed data have since been used for:

- classification (identification of forest, land-use and/or land-cover classes);
- estimation or prediction of continuous parameters, for example timber volume or basal area per hectare.

Classification Studies

Satellite image classification uses spectral information represented by the satellite image spectral bands to classify each individual pixel based on the spectral information stored in the image pixel. This type of classification is termed spectral pattern recognition. In general, the classification process assigns each image pixel to a one landcover (e.g. water, coniferous forest, deciduous forest, corn, wheat, etc.) or landuse (forest agriculture, urban fabric etc.) class. The resulting classified image consists of a mosaic of pixels, each of which belong to a particular theme, and is considered a thematic "map" of the original image. Satellite image classification can be carried out in two ways: unsupervised, where no training or reference information is provided to aid the classification and generally used for exploratory image analysis or, supervised where an expert provides 'ancillary data' to guide the classification algorithm.

The use of imagery acquired by different sensors has led to a range of applications to map forests at different scales. Forest classification over large areas has long been researched to provide broad classifications of forest types. European efforts have included the use of data from the Advanced Very High Resolution Radiometer (AVHRR) sensor system (Häme et al. 2001; Schuck et al. 2003), while more recently this work was extended by Pekkarinen et al. (2009) to improve the classification of European forest cover using Landsat ETM+ data and the Corine Land Cover 2000 (CLC2000) database and a k-means clustering and *k*NN technique. Similar approaches were employed by Hagner and Reese (2007) in Sweden to provide an automatic classification of forest types for use in the CLC database derived from Landsat TM/ETM+ data, field inventory data and a neural network.

Horler and Ahern (1986) utilised spectral radiation data from Landsat TM image scenes as a means of identifying the separability of forest classes in a study area in western Ontario, Canada. Two main techniques were used, namely feature selection and principal components. Feature selection, is a statistical technique that selects a subset of explanatory variables based on their importance to build robust statistical models thereby improving classification performance. Principal component analysis (PCA) is another statistical technique that transforms a number of potentially correlated explanatory variables into a number of uncorrelated bands. This technique is frequently used to reduce or compress the number of explanatory variables into a number of principal components, in which the first two components hold the majority of the information of the entire set of variables. In the above mentioned study, it was found that the best three TM bands (3, 4 & 5) were almost as good as the first three principal components.

Decision tree methods (i.e. techniques that recursively partition a dataset based on binary rules) have been used by researchers to analyse and classify remotely sensed data as an alternative approach to traditional image classification approaches for landcover mapping (Hansen et al. 1996). A non-parametric supervised classification based on a decision tree model was used by Joy et al. (2003) to classify vegetation types in Arizona using field inventory data, Landsat TM imagery and additional spatial data. The overall accuracy achieved was 74.5%, with errors caused by the lack of clear differentiation between mixed conifer and spruce dominated stands. Brown de Coulston et al. (2003) used a decision tree method with field observations and Landsat ETM+ data to map vegetation types in Pennsylvania, USA, and achieved an accuracy of 99.5% when only forest and non-forest classes were considered. Landuse data at different scales were used in conjunction with Landsat data and a regression tree method in the Amazon by Cardille and Clayton (2007) to reinterpret existing land-cover classifications by determining what categories are most highly related to the polygon land-use data across the study area. It is important to point out that the above-mentioned errors are based on the estimation errors that are calculated at a pixel level, i.e. the level of agreement and disagreement between validation pixels with those in the classification. These pixel-based errors do not, however, provide a means of calculating the errors associated with the area estimates of the different vegetation cover types within the study area, which are frequently sought.

Forest Parameter Estimation Studies

With respect to forest parameter estimation, Franklin (1990) concisely summarised the methodology involved in these approaches as follows:

1. Establish a number of field inventory sampling points;
2. Collect forest structure information at these points;
3. Use remotely-sensed satellite imagery, locate the points on the image;
4. Extract the image features relating to each sampling point;
5. Develop the model relating the field data to the image features;
6. Use the model to predict the forest parameters based on the spectral data;
7. Develop and select error estimation methods;
8. Validate the predictions and estimates at pixel level and for different areal units.

Once a suitable model is produced using the image features as explanatory variables, the model is inverted to predict the forest stand characteristics for unsampled forest areas. The range of datasets that have been integrated into these types of inventories is diverse, but in general the modelling techniques have relied on regression models, such as stepwise regression, regression trees, most similar neighbour and k-Nearest neighbour (*k*NN) estimation. However, other techniques such as neural networks (Atkinson and Tatnall 1997) and boosting and bagging (Briem et al. 2002) also exist, whose properties and configurations vary based on the inventory, image and ancillary datasets used.

The integration of remotely sensed satellite imagery with field inventory data for the estimation of forest stand parameters dates back to the 1980s. Forest classification maps were already used effectively for stratification purposes and to plan field surveys, and it soon became clear that spatially explicit estimates of forest parameters would be highly useful to support strategic forest management and planning.

As in all remote sensing applications, the measurement and estimation of forest resources relies on the interactions of electro-magnetic radiation with the target object and subsequent analysis of the returned signal recorded by the sensor. Statistical relationships between the EMR signal and the forest parameters are then analysed. One of the earliest applications in this area was developed by Jaakkola (1983), who used Landsat TM imagery within a multi-stage timber inventory in a study area in Finland. His research consisted of estimating timber volume using regression equations that used the image data as independent variables. Timber volumes of Scots pine and Norway spruce were quantified by Ardo (1992) using the spectral values from Landsat 5 TM imagery for a study area in southern Sweden. Data from 99 randomly selected forest compartments were used to develop a regression model between spectral radiation data and the measured timber volume. The predictions were then compared against 99 forest compartments located within the study area of 1,335 ha for which field data were available and it was found that there was a close correlation between the measurements and predictions.

Häme et al. (1987) used spectral data from three SPOT 1 XS images to estimate stand characteristics ranging in size from 0.5 - 5 ha in Finland. The parameters estimated using regression models included tree stem volume, mean age and mean diameter. It was concluded that better estimates could be achieved using Landsat TM imagery as opposed to SPOT-1 due to the higher spectral resolution of the Landsat data, despite the higher spatial resolution of the latter sensor.

Research in this area continued to be pioneered by Scandinavian researchers, who were first to successfully integrate such a method into a NFI (Tomppo et al. 2008b). The Reference Point Sample (RSP) technique was proposed by Kilkki and Paivinen (2006) as a pixel based approach that assigns known 'reference' pixel data to unknown pixels through a weighting system. This was subsequently refined to integrate additional sources of data and was implemented by Tomppo (1991) on an operational basis within the Finnish National Forest inventory. This technique was and remains fully operational within the Finnish NFI and it has become known as 'Multi-Source National Forest Inventory' (MSFI) (Tomppo 1996), as it not only combines field inventory data with optical satellite imagery, but also uses digital terrain and ancillary spatial data. MSFI is underpinned by k-Nearest Neighbour (*k*NN), a non-parametric statistical estimation technique. The process links field inventory plot data with spectral responses of a satellite image and imputes the known variables of field plots to unsampled forest areas. This basic principle was adapted by other researchers, who proposed methods related to *k*NN, but which differed based on the underlying statistical relationships, e.g. most similar neighbour (Moeur and Stage 1995) and Gradient Nearest Neighbour (GNN) (Ohmann and Gregoire 2002).

The following describes the technique in very broad terms, but for further details on this technique, the reader should consult the following references (Fix and Hodges, 1951). However, in very broad terms the technique utilises two sets of observations, the first, the reference dataset contains the spatial location of the NFI plot, forest parameter plot estimate and associated spectral information retrieved from the satellite image based on its pixel or neighbourhood of pixels. The set of target pixels consists of all unsampled forest pixels for which a forest parameter estimate is sought. Each target pixel is assigned a weighted average of the plot level forest variables calculated from a subset of the reference data set that consists of the nearest pixels, based on the similarity of pixels in their spectral information. This basic principle was adapted by other researchers, who proposed methods related to *k*NN, but which differed based on the underlying statistical relationships, e.g. most similar neighbour (Moeur and Stage 1995) and Gradient Nearest Neighbour (GNN; Ohmann and Gregoire 2002).

Due to its transparency and success, the MSFI approach was adopted and adapted to a variety of forest conditions. The Swedish Forest Authorities applied the technique within their NFI (Holmgren et al. 2000; Nilsson 2002) using a range of image datasets, but primarily using Landsat TM/ETM+, and more recently SPOT 4/5 XS imagery. The outputs from the Swedish MSFI have been applied to habitat modelling for moose and birds by Reese et al. (2002). The MSFI technique has been widely tested throughout the world: in New Zealand to assist in their preharvest inventory, where it was applied to a 1,000 ha block of Radiata pine (Tomppo et al. 1999), in Norway (Gjertsen et al. 1999; Gjertsen 2007), in Mediterranean forest conditions in Italy to estimate basal area using Landsat 7 ETM+ data (Maselli et al. 2005; Baffetta et al. 2009), in central Europe where Koukal et al. (2005) tested the influence of radiometric calibration on forest estimates in the Austrian NFI, and for mapping temperate forest types in Scotland (McInerney and Suarez 2005).

A recent research area has focused specifically on the error estimation techniques employed in remote sensing. Rather than only considering the calculation of errors (RMSE and associated standard errors) at pixel level, the use of measures to determine the uncertainty of predictions and/or classifications over larger geographic areas, extending outside of the study region, has been investigated. This is considered a necessary extension to the validation of remote sensing analysis as pixel based estimation techniques provide only necessary measures for individual study areas, and cannot often be used to make direct inferences over larger areas. Some examples of these types of calculations can be found in McRoberts et al. (2002), Tomppo and Halme (2004) and Kim and Tomppo (2006).

It is evident from the above review that optical satellite imagery is being widely used to assist in the monitoring of forests and in the measurement of forest parameters. Similarly, a wide range of traditional as well as new statistical techniques have been employed in the analysis of satellite imagery, in conjunction with field inventory data, while a variety of ancillary datasets have also been integrated in the analysis procedures to improve the estimation of forest parameters and prediction of forest variables through pre- and post-stratification approaches.

Remote Sensing studies in Ireland

Over the past two decades a number of forestry remote sensing projects have been carried out in Ireland, primarily to assess the spatial distribution and composition of forest stands. The Department of Agriculture, Fisheries and Food continues to make operational use of Ordnance Survey Ireland (OSi) digital aerial photographs for the monitoring of the national forest estate, in particular to update forest vector maps and for pre-stratification of national forest inventory plots (Forest Service 2007).

The largest national remote sensing project that was carried out in Ireland resulted in the creation of the Forest Inventory and Planning Systems (FIPS) datasets in 1998. This project was lead by the Irish Forest Service with support from Coillte Teoranta, the European Commission's Joint Research Centre in Italy and the National Remote Sensing Centre in the United Kingdom. Twenty forest development classes were mapped across Ireland using medium resolution optical satellite imagery from the Landsat TM sensors and digital aerial photographs. The satellite images were classified using a two-phase process consisting of a neural network and a maximum likelihood classification, which was carried out using SILVICS (McCormick and Folving 1998; Gallagher et al. 1999). The FIPS project superseded two pilot projects that had established the usefulness of remote sensing and digital spatial data for the identification of the spatial distribution of forest stands in Ireland (MacSiúrtaín et al. 1994).

Following on from the development of FIPS, the Irish Forest Soils project was carried out by researchers at Teagasc to create a series of national, digital thematic maps that included a soil classification map, a map of parent materials and a landcover map (Bulfin et al. 2002; Loftus et al. 2002). These maps were produced through the use of satellite image classification and photogrammetric techniques, based on OSi aerial photography, digital terrain data and Landsat 5 TM imagery.

Coillte Teoranta conducted a research study that focussed on the estimation of forest health in coniferous plantations using colour infra-red photography (Stanley et al. 1996). In particular, the research exploited the use of the infra-red band of the aerial photos to assess the extent of discolouration within the foliage of coniferous tree species.

More recently, a number of research studies have been carried out to evaluate the use of remote sensing for forest mapping and monitoring. McInerney and Nieuwenhuis (2009) estimated standing volume and basal area per hectare using field inventory data from the Irish NFI, medium resolution optical satellite imagery from the SPOT 4/5 sensors and ancillary spatial data. Pixel based estimates of the two above mentioned parameters were calculated for unsampled forest pixels (i.e. pixels with no NFI information) using two supervised non-parametric techniques, namely *k*NN estimation and the Random Forest algorithm in regression mode (Breiman 2001). These techniques can be considered to be "supervised" in so far as a reference set of variables is used to impute values across the forest areas of the satellite image, based on a weighted average of the reference data. The weighted average is calculated based on the spectral similarity of the unsampled forest pixel to observations in the reference set. Within the study, it was found that at a pixel level, the relative Root Mean Square Errors (RMSEs) were approximately 50 – 59% for volume and basal area per hectare in a study area in the mid-west of Ireland. This research demonstrated that it is possible to regionalise NFI stand parameters using medium resolution satellite imagery. In particular, it demonstrates that it can produce more detailed, spatially referenced forest resource information at a regional scale than could be achieved from the sole use of NFI data. With some refinements, the methodology could be used on an operational basis to support field-based forest inventories in Ireland. In order to achieve this, it will be necessary to produce areal based estimation errors over large areas, e.g. at provincial and national levels, in addition to the pixel based estimation errors presented above.

As part of the Global Monitoring and Environmental Security (GMES) Service Element, a consortium lead by Metria, a Swedish Geomatics company, and supported by University College Dublin and the Irish Forest Service, carried out an image classification of Landsat TM/ETM+, SPOT 4/5 and IRS images for two study areas in Ireland, namely county Wicklow and parts of Mayo/Roscommon. The focus of the study was to produce a high resolution forest mask using a minimum map unit of 1 ha for three time dates: 1990, 2000 and 2006 (McInerney et al. 2010b). In particular, the project sought to map and quantify forest change, focusing in particular on afforestation on peatland areas and changes in forest cover during the 16-year period. Such research demonstrates the way in which LULUCF can be measured using archived satellite imagery and provide much needed information on the state of Irish forests.

LiDAR

In recent years, light detection and ranging (LiDAR) data has gained considerable interest. This is due to the high quality and resolution of the returned datasets, which consist of three-dimensional point data from the top of the vegetative surface (Digital Surface Model) and non-vegetated surface (Digital Terrain Model). The datasets consist of points that are precisely located using a differential GPS and highly precise timing clock. Figure 1 provides a simplified overview of the processing of airborne

LiDAR data to derive forest based metrics. Raw LiDAR data are acquired over an area, with the raw data analysed within a processing system. The dataset consists of a first return, representing the top of the vegetation canopy, and a last return, representing the ground surface. In general, these returns are filtered to remove any anomalies and are interpolated to produce a continuous surface of values. These interpolated dataset produce the digital terrain model (DTM) and the digital surface model (DSM). The subtraction of the DTM from the DSM results in the canopy height model (CHM), which can be considered a digital representation of the top of the vegetation canopy or of the dominant trees. By using region growing and pattern recognition techniques, it is possible to identify individual trees and to delineate tree canopies within the canopy height model (Figure 2).

Numerous studies have demonstrated the use of airborne LiDAR to estimate forest stand metrics, such as stand canopy height (Gobakken and Naesset 2004; Naesset 1997), individual tree heights (Suarez et al. 2005), above-ground biomass (Patenaude et al. 2004) and species classification (Moffiet et al. 2005). Clifford et al. (2010) demonstrated the use of LiDAR for a study area in Ireland and determined that the LiDAR-derived estimates of tree height compare very favourably with conventional field based measurements. A recent review article by van Leeuwen and Nieuwenhuis (2009) summarises studies on space-borne, airborne and terrestrial LiDAR applications in forestry worldwide and the potential of these different LiDAR sensors, on their own or in combination with each other, to derive detailed measurements of trees and forest stands.

It is clear that LiDAR can provide detailed information on the structure of forest resources. In particular, tree height, crown dimensions and species can be separated using information on branch and leaf structure. However, one of the principal limitations to the operational use of LiDAR in forestry is the cost per unit area in acquiring data, with the general rule: the more detailed the data (i.e. more points per unit area), the more costly it is. However, it has been demonstrated that sub-sampling the dataset can reduce the acquisition cost and that it is possible to combine the sample of high resolution LiDAR data with optical satellite imagery to regionalise the information over larger areas using statistical estimation techniques, thus reducing the extent of and cost associated with the initial data requirement (Hudak et al. 2002; McInerney et al. 2010a).

Terrestrial LiDAR

In recent years, research has been carried out to produce three dimensional scans of forest resources using terrestrial scanners (Nieuwenhuis 2008). Terrestrial scanners are mounted on tripods and utilise the same technology as airborne LiDAR scanners. They produce a fully three-dimensional dataset and to eliminate the problem of occlusion (where one tree blocks the view from the scanner to another tree), multiple scans are acquired from different locations within the forest plot, which are subsequently 'stitched' together. Using semi-automatic methods, it is possible to derive detailed individual tree based measurements relating to diameter at breast height, stem straightness, taper and branchiness, as well as non-timber information such as understory structure, deadwood and terrain classification (Bienert et al. 2006,

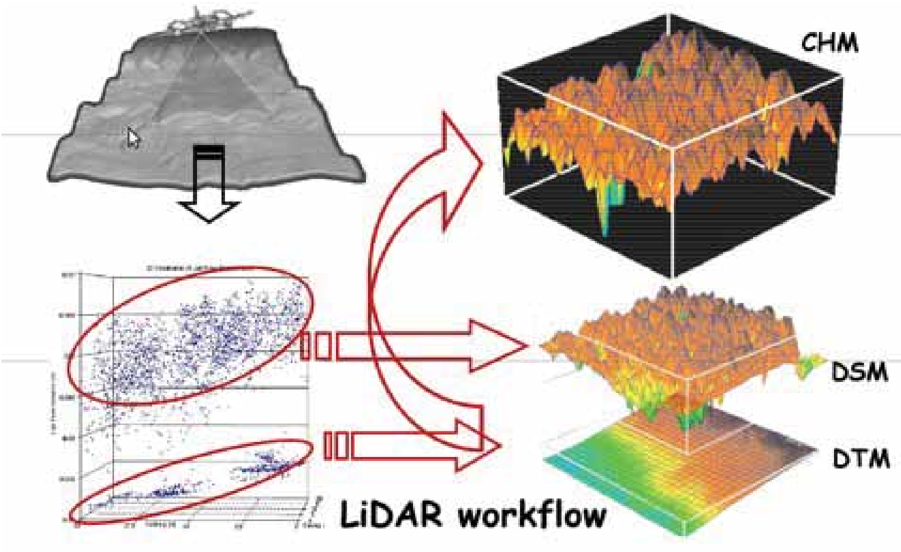

Figure 1: *Airborne LiDAR processing workflow.*

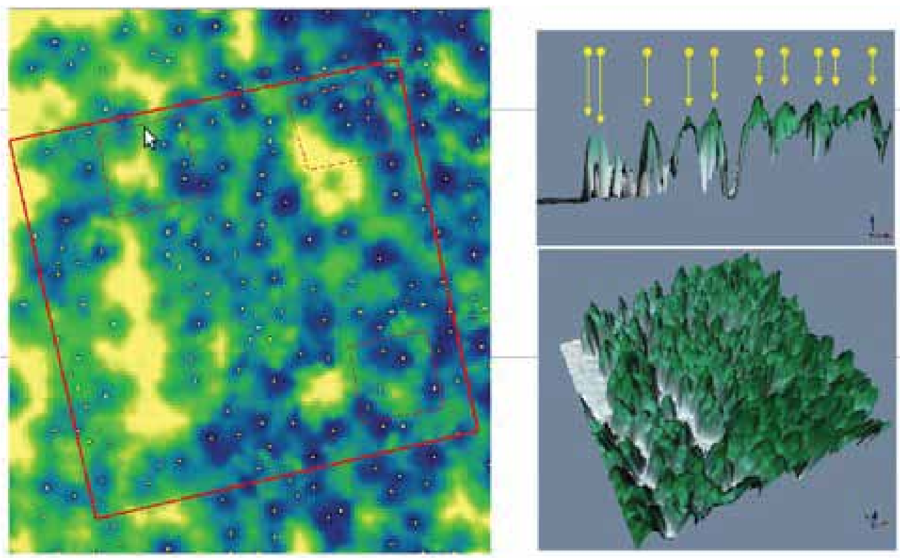

Figure 2: *Individual tree identification from LiDAR derived CHM*.

van Leeuwen and Nieuwenhuis 2010). This clearly offers many new opportunities in the acquisition of forest field information. The datasets are fully objective and provide extremely detailed information, which can be used to support forest inventories, as well as timber allocation and processing procedures (Keane 2007, Murphy et al. 2010). However, there are some specific disadvantages in the use of these sensors that relate to acquisition time, limitations in the use of these sensors in some specific site and forest conditions and the need to further develop and refine detailed processing algorithms that can be used to pre-process and retrieve tree measurements (Nugent et al. 2009).

Conclusions and implications for operational use in Ireland

There is an implicit need for all forests at global, national and regional levels to be managed in a sustainable manner. Forest resources are changing at an increasing rate, due to more intensive management practices, storm and fire damage, effects from insects and diseases, and the consequences of climate change. In order to successfully monitor these changes over time in an objective, transparent and effective way, foresters require access to timely and objective information, which can only be obtained through the use of remote sensing. However, it would be incorrect to consider optical satellite imagery as a perfect imaging solution for the purposes of forest or indeed environmental monitoring. It is a science and technology that is continually evolving, but it also still has some inherent limitations that vary based on its field of use and geographic application area.

One of the main limitations in the use of remote sensing data in operational contexts is the difficulty of acquiring cloud-free satellite imagery over Ireland and other northern countries with temperate climates. With the current configuration of imaging satellites, this can mean that only three or four useable scenes are acquired during any one year.

The stability and continuity of satellite sensor missions has to be borne in mind when data are used within operational contexts. For instance, the failure of the Scan Line Corrector on-board the Landsat 7 ETM+ sensor (one of the most widely used satellite sensors for environmental and land monitoring) meant that the data acquired from this sensor were virtually unusable from 2004 onwards. A related issue was the fact that Landsat satellites were no longer being developed by the Government of the United States of America and this raised many questions regarding data availability and continuity of missions by the remote sensing community that was heavily dependent on this satellite.

In Ireland, the current generation of optical imaging satellites has limitations in clearly distinguishing young forest plantations from other land-cover types (such as scrub or rough agricultural land). This difficulty is caused by the mixed spectral resolution returned from the underlying ground vegetation and it is only possible to accurately classify the forest stand once it has matured to the point of canopy closure.

Despite the description of numerous examples of the use of remote sensing in forest applications, there still remains a reluctance to use remote sensing in many operational environments, despite the widespread use of aerial photographs by foresters. To an extent, it is true that remote sensing has remained a research discipline that is focussed on scientific methods to analyse and interpret images. Nevertheless, examples cited in this article illustrate the fact that remote sensing is an active component within operational forest monitoring and inventory programmes. In addition, over the last five years, Earth observation data have become almost ubiquitous within every day life through technologies such as Google Earth, Google Maps, Bing Maps and related web data services.

It continues to be necessary to bridge the gap in knowledge between foresters and remote sensing analysts to more successfully integrate remote sensing and forest management in Ireland. The recent generation of high spatial resolution satellite sensors, such as the Quickbird, Ikonos and GeoEye, offer equivalent, if not better image information for the same or lower costs when compared to aerial photographs. Moreover, the synoptic view offered by satellite images and the higher frequency of image acquisition make spaceborne satellite imagery more useful in operational settings. Within the context of forest monitoring and national forest inventory programmes, it is widely considered by the Scandinavian countries that remote sensing can substantially increase the cost-efficiency of an inventory. With these factors in mind, it is useful to outline some of the noteworthy new remote sensing technological developments of relevance to forestry:

1. Global daily coverage from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, which acquires data across 36 spectral bands at a resolution of 250, 500 and 1,000 m. As a result, it can provide dynamic larges-scale information on the state of forests;
2. Hyperspectral imaging sensors, which provides extremely high spectral resolution satellite imagery. For instance, a hyperspectral sensor could acquire 217 spectral bands within the spectral range of one image band from a medium resolution sensor, such as Landsat or SPOT. This increased spectral information can enable the extraction of very subtle differences between species, forest condition and health;
3. Synthetic Aperture Radar sensors, which are weather and light independent and are being increasingly used within forest resource assessments, particularly for the retrieval of tree height and stand structure. These sensors have being launched on-board ESA's Envisat sensor, as well as Japan's ALOS and Radarsat-2;
4. Combined use of terrestrial and airborne LiDAR, coupled with high spatial resolution satellite imagery, in order to improve the quality of the tree and stand derived information from above and below the canopy, thereby providing the most comprehensive tree-related information;
5. New commercial imaging sensors, such as GeoEye-1, WorldView-1 and Quickbird are offering very high resolution satellite imagery (50 – 61 cm spatial resolution), with the ability for the sensors to return to the same location at shorter temporal intervals;
6. European Space Agency's (ESA) Sentinel missions.

With respect to the last point, the European Space Agency has a short-to-medium term plan to launch five satellite sensors, which will be known as Sentinels, for the specific operational needs of the European Commission and European Space Agency Global Monitoring for Environmental Security (GMES) programme. Sentinel 2 will provide high-resolution multispectral imagery that will be used to monitor vegetation, soil and water bodies. The other Sentinel sensors will focus on atmospheric monitoring, and land and sea/ocean surface temperature monitoring using RADAR instruments.

Image quality and processing requirements are linked. As the spatial and spectral resolutions increase, the size of the datasets increases at an exponential rate. The requirements for more sophisticated computer processing and storage facilities will increase likewise. The image processing and analysis techniques are also developing in line with the developments of imaging sensors. In particular, the use of techniques such as *k*NN for parameter estimation will provide novel approaches to utilize disparate data sources in an efficient way to improve the spatial estimation of parameters. With the correct data sources, these techniques could be further developed to upscale high-resolution forest monitoring data, acquired from the ICP Level II plots in Ireland, over small homogeneous forest areas.

Despite the advances in the technology of space and airborne sensors, it is necessary to bear in mind that there always remains a need for field inventories, to train sophisticated statistical modeling tools and validate results derived from remote sensing analyses. However, the use of new satellite sensors and image analysis techniques, coupled with the needs and expertise of forest managers, can lead to the development of new applications to provide more comprehensive information for the sustainable management of the Irish forest estate.

References

Ardo, J. 1992. Volume Quantification of coniferous forest compartments using spectral radiance recorded by Landsat Thematic Mapper. *International Journal of Remote Sensing* 13: 1779–1786.

Atkinson, P. and Tatnall, A. 1997. Introduction to Neural Networks in remote sensing. *International Journal of Remote Sensing* 18: 699-709.

Baffetta, F., Fattorini, L., Franceschi, S. and Corona, P. 2009. Design-based approach to *k*-nearest neighbours technique for coupling field and remotely sensed data in forest surveys. *Remote Sensing of Environment* 113: 463-475.

Bienert, A., Scheller, S., Keane, E., Mullooly, G. and Mohan, F. 2006. Application of terrestrial laserscanners for the determination of forest inventory parameters. In *International Archives of Photogrammetry, Remote Sensing, and Spatial Information Sciences* Vol. XXXVI, Part 5. http://www.isprs.org/commission5/proceedings06/paper/1270_Dresden06.pdf/

Breiman, L. 2001. Random Forests. *Machine Learning* 5 (1): 5-32.

Briem, G.J., Benediktsson, J.A. and Sveinsson, J.R. 2002. Multiple classifiers applied to multisource remote sensing data. *IEEE Transactions on Geoscience and Remote Sensing* 40: 2291-2299.

Brown de Coulston, E., Story, M., Thompson, C., Commisso, K., Smith, T. and Irons, J. 2003. National Park Vegetation Mapping Using Multitemporal Landsat 7 data and a decision tree classifier. *Remote Sensing of Environment* 85: 316-327.

Bulfin, M., Farrelly, N., Fealy, R., Green, S., Loftus, M., Meehan, R. and Radford, T. 2002. The Irish Forest Soils Project (FIPS–IFS). *Irish Scientist*.

Campbell, J. 2002. *Introduction to Remote Sensing*. Taylor and Francis, London, England.

Cardille, J. and Clayton, M. 2007. A regression tree-based method for integrating land-cover and land-use data collected at multiple scales. *Environmental Ecology Statistics* 14: 161–179.

Clifford. B., Farrelly, N. and Green, S. 2010. A preliminary evaluation of the application of multi-return LiDAR for forestry in Ireland. *COFORD Connects* Silviculture / Management No. 18. http://www.coford.ie/media/coford/content/publications/projectreports/cofordconnects/sm18.pdf Retrieved on 10th October 2011.

Forest Service. 2007. National Forest Inventory, Republic of Ireland – Methodology. Department of Agriculture, Fisheries and Food. Johnstown Castle Estate, Co. Wexford.

Fix, E. and Hodges, J. 1951. Discriminatory analysis - nonparametric discrimination: consistency properties. Project 41-49-004, Report 4, pp. 261–279.

Franklin, S.E. 1990. *Remote Sensing for Sustainable Forest Management*, 4th Ed. Lewis Publishers, Florida, USA.

Gallagher, G., Dunne, S., Jordan, P. and Stanley, B. 1999. Ireland's Forest Inventory and Planning System. In *Proceedings of the IUFRO Conference on Remote Sensing and Forest Monitoring*. June 1-3, 1999. Rogow, Poland.

Gobakken, T. and Naesset, E. 2004. Estimation of diameter and basal area distributions in coniferous forests by means of airborne laser scanner data. *Scandinavian Journal of Forest Research* 19: 529-542.

Gjertsen, A.K., Tomppo, E. and Tomter, S. 1999. National Forest Inventory in Norway: Using Sample Plots, Digital Maps and Satellite Images. In *Proceedings of the IEEE International Geosciences and Remote Sensing Symposium*, Hamburg, Germany, pp. 729-731.

Gjertsen, A.K. 2007. Accuracy of forest mapping based on Landsat TM data and a *k*NN-based method. *Remote Sensing of Environment* 110: 420-430.

Hagner, O. and Reese, H. 2007. A method for calibrated maximum likelihood classification of forest types. *Remote Sensing of Environment* 110: 438-444.

Häme, T., Tomppo, E. and Parmes, E. 1987. Stand based forest inventory and monitoring using SPOT image. In *Proceedings of the International Conference SPOT-1 Image Utilisation*, Assessment, Results, 23 - 27 November, Paris, France, pp. 971-977.

Häme, T., Stenberg, P., Anderson, K., Rauste, Y., Kennedy, P., Folving, S. and Sarkeala, J. 2001. AVHRR-based forest proportion map of the Pan-European area. *Remote Sensing of Environment* 77: 76-91.

Hansen, M., Dubayah, R. and DeFries, R. 1996. Classification trees: an alternative to traditional land cover classifiers. *International Journal of Remote Sensing* 17: 1075-1081.

Holmgren, J., Joyce, S., Nilsson, M. and Olsson, H. 2000. Estimation and mapping of forest stand density, volume and cover type using the k-Nearest Neighbour method. *Scandinavian Journal of Forest Research* 15: 103-111.

Horler, D. and Ahern, F. 1986. Forestry information content of Thematic Mapper data. *International Journal of Remote Sensing* 3: 405-428.

Hudak, A., Lefsky, M., Cohen, W. and Berterretche, M. 2002. Integration of lidar and Landsat ETM+ data for estimating and mapping forest canopy height. *Remote Sensing of Environment* 82: 392-416.

Jaakkola, S. 1983. Use of the Landsat MSS for forest inventory and regional management: the European experience. *Remote Sensing Reviews* 2: 165-213.

Joy, S., Reich, R. and Reynolds, R. 2003. A non-parametric, supervised classification of vegetation types on the Kaibab National Forest using decision trees. *International Journal of Remote Sensing* 24: 1835-1852.

Keane, E. 2007. The potential of terrestrial laser scanning technology in pre-harvest timber measurement operations. *COFORD Connects*, Harvesting / Transportation no. 7. COFORD, Dublin. http://www.coford.ie/media/coford/content/publications/projectreports/ Retrieved 10th October 2011.

Kilkki, P. and Paivinen, R. 2006. Reference sample plots to combine field measurements and satellite data in forest inventory. Technical report, Dept. of Forest Mensuration and Management, University of Helsinki, Finland.

Kim, H.-J. and Tomppo, E. 2006. Model-based prediction error uncertainty estimation for *kNN* method. *Remote Sensing of Environment* 104: 257-263.

Koukal, T., Suppan, F. and Schneider, W. 2005. The impact of radiometric calibration on *k*NN predictions of forest attributes. In *Proceedings of the ForestSAT* 2005 Conference, 31st May - 3rd June, Boras, Sweden.

Lillesand, T.M., Kiefer, R.W. and Chipman, J.W. 2008. *Remote sensing and image interpretation*. 6th Ed. John Wiley & Sons, Hoboken, New Jersey.

Loftus, M., Bulfin, M., Farelly, N., Fealy, R., Green, S., Meehan, R. and Radford, T. 2002. The Irish forest soils project and its contribution to the assessment of biodiversity. *Biology and Environment: Proceedings of the Royal Irish Academy* 102: 151-164.

Lund, H.G. Befort, W., Brickell, J., Ciesla, W., Collins, E., Czaplewski, R., Disperati, A., Douglass, R., Dull, C., Greer, J., Hershey, R., LaBau, V., Lachowski, H., Murtha, P., Nowak, D., Roberts, M., Schram, P., Shedha, M., Singh, A. and Winterberger, K. 1997. Forestry. In *Manual of Photographic Interpretation*, 2nd Edition. Bethesda, MD: American Society for Photogrammetry and Remote Sensing. Ed. Philipson, W.R., pp. 399-440.

Maselli, F., Chirici, G., Bottai, L., Corona, P. and Marchetti, M. 2005. Accuracy of forest mapping based on Landsat TM data and a kNN-based method. *International Journal of Remote Sensing* 17: 3781-3796.

McCormick, N. and S. Folving. 1998. Monitoring European forest biodiversity at regional scales using satellite remote sensing. In *Assessment of Biodiversity for Improved Forest Planning*. Eds. Bachmann, P., Kohl, M. and Paivinen, R. Kluwer Academic Publishers, Dordrecht, The Netherlands.

McInerney, D. and Suarez, J. 2005. Scottish forest inventory information derived from satellite imagery and field data. In Proceedings of IUFRO Conference "*Sustainable Forestry in Theory and Practice*", Edinburgh, 5-8 April 2005.

McInerney, D. and Nieuwenhuis, M. 2009. Comparative Analysis of *k*NN and Decision Tree Methods for the Irish NFI. *International Journal of Remote Sensing* 30: 4937–4955.

McInerney, D., Suarez, J., Valbuena, R. and Nieuwenhuis, M. 2010a. Forest canopy height retrieval using LiDAR data, medium resolution satellite imagery and kNN estimation in Aberfoyle, Scotland. *Forestry* 83: 195-206.

McInerney, D., Harper, C. and Nieuwenhuis, M. 2010b. Monitoring forest cover in Ireland - Validation of new remote sensing data. Poster presented at the workshop: "Forest monitoring network Workshop. The value of forest monitoring networks: Their role in a changing environment" Glenview Hotel, Delgany, Co. Wicklow, 4 March 2010. Hosted by COFORD.

McRoberts, R.E., Wendt, D.G., Nelson, M.D. and Hansen, M.D. 2002. Using a land cover classification based on satellite imagery to improve the precision of forest inventory area estimates. *Remote Sensing of Environment* 81: 36-44.

McRoberts, R.E. and Tomppo, E.O. 2007. Remote sensing support for national forest inventories. *Remote Sensing of Environment* 110: 412-419.

McRoberts, R.E. 2008. Using satellite imagery and the k-nearest neighbours technique as a bridge between strategic and management forest inventories. *Remote Sensing of Environment* 112: 2212-2221.

Mac Siúrtáin, M.P., Flanagan, E.S., Collins, E.S., Jordan, P., Little, D. and Joyce, P.M. 1994. National Forest Inventory Pilot Project -Roscommon, Final Report, University College Dublin.

Moeur, M. and Stage, A. 1995. Most Similar Neighbour: An Improved Sampling Inference Procedure for Natural Resource Planning. *Forest Science* 41: 337-359.

Moffiet, T., Mengersen, K., Witte, C., King, R. and Denham, R. 2005. Airborne laser scanning: exploratory data analysis indicates potential variables for classification of individual trees or forest stands according to species. *ISPRS Journal of Photogrammetry and Remote Sensing* 59: 289-309.

Murphy, G., Lyons, J., O'Shea, M., Mullooly, G., Keane, E. and Devlin, G. 2010. Management tools for optimal allocation of wood fibre to conventional log and bio-energy markets in Ireland: a case study. *European Journal of Forest Research* 129: 1057-1067.

Naesset, E. 1997. Determination of mean tree height of forest stands using airborne laser scanner data. *ISPRS Journal of Photogrammetry and Remote Sensing* 52: 49-56.

Nilsson, M. 2002. Deriving Nationwide estimates of forest variables for Sweden using Landsat ETM+ and field data. In *Proceedings of the ForestSAT 2002 Symposium*, 5th - 9th August, Edinburgh, Scotland.

Nieuwenhuis, M. 2008. FORESTSCAN – Terrestrial Laser Scanning Technology for Multi-Resource Inventories. *Irish Timber and Forestry* 17: 32-35.

Nugent, C., Bridge, D., Murphy, G. and Oyen, B. 2009. Case-Based Support for Forestry Decisions: *How to See the Wood from the Trees*. ICCBR 2009 LNAI 5650, pp 479-493.

Ohmann, J. and Gregoire, M. 2002. Predictive mapping of forest composition and structure with direct gradient nearest neighbour imputation in coastal Oregan, U.S.A. *Canadian Journal of Forest Research* 32: 725-741.

Patenaude, G., Hill, R., Milne, R., Gaveau, D., Briggs, B. and Dawson, T. 2004. Quantifying forest aboveground carbon content using LiDAR remote sensing. *Remote Sensing of Environment* 93: 368-380.

Pekkarinen, A., Reithmaier, L. and Strobl, P. 2009. Pan-European forest/non-forest mapping with Landsat ETM+ and CORINE Land Cover 2000 data. *ISPRS Journal of Photogrammetry and Remote Sensing* 64: 171-183.

Reese, H., Nilsson, M., Sandstrom, P. and Olsson, H. 2002. Applications using estimates of forest parameters derived from satellite and forest inventory data. *Computers and Electronics in Agriculture* 37: 37-55.

Schuck, A., Päivinen, R., Häme, T., Van Brusselen, J., Kennedy, P. and Folving, S. 2003. Compilation of a European forest map from Portugal to the Ural mountains based on earth observation data and forest statistics. *Forest Policy and Economics* 5: 187-202.

Stanley, B., Dunne, S. and Keane, M. 1996. Forest condition assessments and other applications of colour infrared (CIR) aerial photography in Ireland. *Irish Forestry* 53: 19-27.

Suárez, J.C., Ontiveros, C., Smith, S. and Snape, S. 2005. Use of airborne LiDAR and aerial photography in the estimation of individual tree heights in forestry. *Computers and Geosciences* 31: 253-262.

Tomppo, E. 1991. Satellite Image Based National Forest Inventory of Finland. *International Archives of Photogrammetry and Remote Sensing* 28: 419-424.

Tomppo, E. 1996. Application of Remote Sensing in Finnish National Forest Inventory. In *Proceedings of the Application of Remote Sensing in European Forest Monitoring*, 14-16 October 1996, Vienna, Austria, pp. 147–156.

Tomppo, E., Goulding, C. and Katila, M. 1999. Adapting Finnish multi-source forest inventory techniques to the New Zealand preharvest inventory. *Scandinavian Journal of Forest Research* 14: 182-192.

Tomppo, E. and Halme, M. 2004. Using coarse scale forest variables as ancillary information and weighting of variables in *k*-NN estimation: a genetic algorithm approach. *Remote Sensing of Environment* 92: 1-20.

Tomppo, E., Olsson, H., Ståhl, G., Nilsson, M., Hagner, O. and Katila, M. 2008a. Combining national forest inventory field plots and remote sensing data for forest databases. *Remote Sensing of Environment* 112: 1982-1999.

Tomppo, E., Haakana, M., Katila, M. and Peräsaari, J. 2008b. Multi-source national forest inventory -Methods and applications. *Managing Forest Ecosystems* 18. Springer. 374 p.

Van Leeuwen, M. and Nieuwenhuis, M. 2010. Retrieval of forest structural parameters using LiDAR remote sensing. *European Journal of Forest Research* 129: 749-770.

Varjo, J. 1996. Controlling continuously updated forest data by satellite remote sensing. *International Journal of Remote Sensing* 17: 43-67.

World Bank. 2008. Forest Sourcebook -Practical Guidance for Sustaining Forests in Development Cooperation ISBN 978-0-8213-7163-3.

Wynne, R.F., Oderwald, R.G., Reams, G.A. and Scrivani, J.A. 2000. Optical remote sensing for forest area estimation. *Journal of Forestry* 98: 31-36.