EBONE

European Biodiversity Observation Network:

Design of a plan for an integrated biodiversity observing system in space and time

D5.5: Report on the technical best integration in GEO data streams of current and future EO data sources in and outside EU.

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1. Introduction

The **European Biodiversity Observation Network** (EBONE) is a European contribution on terrestrial monitoring to GEO BON, the Group on Earth Observations Biodiversity Observation Network. EBONE's aims are to develop a system of biodiversity observation at regional, national and European levels by assessing existing approaches in terms of their validity and applicability starting in Europe, then expanding to regions in Africa. The objective of EBONE is to deliver:

1. A sound scientific basis for the production of statistical estimates of stock and change of key indicators;
2. The development of a system for estimating past changes and forecasting and testing policy options and management strategies for threatened ecosystems and species;
3. A proposal for a cost-effective biodiversity monitoring system.

There is a consensus that **Earth Observation (EO) has a role to play in monitoring biodiversity**. With its capacity to observe detailed spatial patterns and variability across large areas at regular intervals, our instinct suggests that EO could deliver the type of spatial and temporal coverage that is beyond reach with in-situ efforts. Furthermore, when considering the emerging networks of in-situ observations, the prospect of enhancing the quality of the information whilst reducing cost through integration is compelling. This report gives a **realistic assessment** of the role of EO in biodiversity monitoring and the options for integrating in-situ observations with EO within the context of the EBONE concept (cfr. EBONE-ID1.4). The assessment is mainly based on a set of targeted pilot studies. Building on this assessment, the report then presents a series of **recommendations** on the best options for using EO in an effective, consistent and sustainable biodiversity monitoring scheme.

The **issues** that we faced were many:

1. Integration can be interpreted in different ways. One possible interpretation is: the combined use of independent data sets to deliver a different but improved data set; another is: the use of one data set to complement another dataset.
2. The targeted improvement will vary with stakeholder group: some will seek for more efficiency, others for more reliable estimates (accuracy and/or precision); others for more detail in space and/or time or more of everything.
3. Integration requires a link between the datasets (in-situ and EO). The strength of the link between reflected electromagnetic radiation and habitats and biodiversity observed in-situ is function of many variables, for example: the spatial scale of the observations; timing of the observations; the adopted nomenclature for classification; the complexity of the landscape and the environmental variability; the habitat and land cover types under consideration.
4. The type of the EO data available varies (function of e.g. budget, size and location of region, cloudiness, national and/or international investment in airborne campaigns or space technology) which determines its capability to deliver the required output.

EO and in-situ could be combined in different ways, depending on the type of integration we wanted to achieved and the targeted improvement. We aimed for an improvement in precision (i.e. the reduction in error of our indicator estimate calculated for an environmental zone).

EBONE in its initial development, focused on three main indicators covering:

(i) the extent and change of habitats of European interest in the context of a general habitat assessment;
(ii) abundance and distribution of selected species (birds, butterflies and plants); and
(iii) fragmentation of natural and semi-natural areas.

For **habitat extent,** we decided that it did not matter how in-situ was integrated with EO as long as we could demonstrate that acceptable accuracies could be achieved and the precision could consistently be improved. The nomenclature used to map habitats in-situ was the General Habitat Classification. We considered the following options where the EO and in-situ play different roles:

- using in-situ samples to re-calibrate a habitat map independently derived from EO;
- using an independent but less accurate EO layer characterising the general spatial variability in cover to post-stratify the in-situ samples;
- using in-situ samples to train the classification of EO data into habitat types where the EO data delivers full coverage or a larger number of samples.

For some of the above cases we also considered the impact that the **sampling strategy** employed to deliver the samples would have on the accuracy and precision achieved.

The indicator ‘ abundance and distribution of selected species
With respect to the indicator ‘**fragmentation**’, we investigated ways of delivering EO derived **measures of habitat patterns** that are meaningful to sampled in-situ observations.

2. Habitat extent - The link between in-situ observations and Earth observation.

2.1. Mapping according to a habitat classification system

EO instruments record reflected, scattered or emitted electromagnetic signals which vary in function of the physical and chemical properties of the viewed surface type. Two types of information can be derived from EO data (Figure 1): quantitative measures of these physical or chemical properties (i.e. a map of for example soil moisture, surface temperature or canopy cover) or a map of thematic classes representing areas with similar reflected, scattered or emitted electromagnetic signals, texture, patterns or shapes. EO derived products of land cover, habitats and species (flora) belong to the second category.

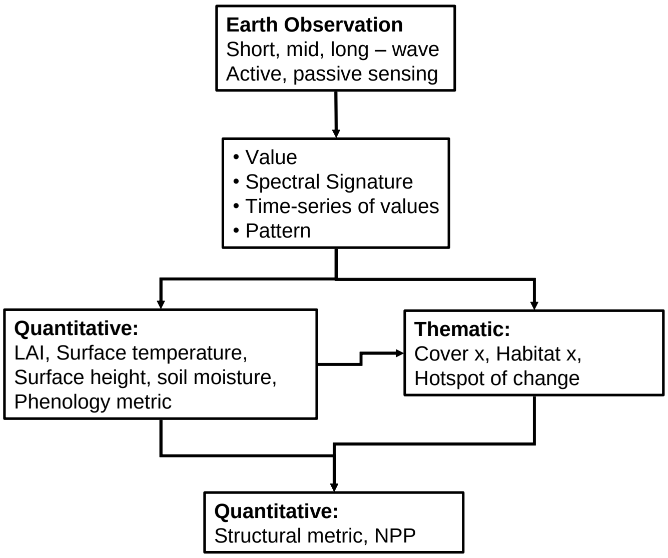

Figure 1: Schematic illustrating the difference between the quantitative and thematic measures derived from Earth Observation.

The observation and recording of land cover, habitats and species require classification systems. Their design results from a compromise between scope of use, level of detail and spatial application. EO introduces not only full area and frequent coverage, but also a new and unique set of classification parameters, such as, reflectance, texture, height or patterns. The degree in which a relationship can be established between electromagnetic signals and the thematic classes (e.g. physiognomic, floristic or ecological) required by the biodiversity monitoring community, will determine the usefulness of the EO derived thematic maps. However, depending on the role EO is being assigned the strength of this relationship needed for a successful outcome will vary (see section 3).

The quality and detail achieved when mapping land cover using EO is primarily limited by the manner in which the electromagnetic radiation interacts with the physical and chemical properties of the land surface. In other words, if habitat classes of interest respond similarly across the whole spectrum in terms of visible and near-infrared reflectance, thermal emission, and microwave scattering, separating these into distinct classes on a map using EO is not feasible. By adopting an EO based perspective of habitats it is possible to predict the EO mapping success for classes of existing habitat nomenclatures (Medcalf et al. 2011). For example, in the case of grassland types, spectral variability is expected to be influenced by, amongst others, the ratio of living plant material to dead plant material; the proportion of plants with horizontal leaves as opposed to upright leaves; the productivity of the vegetation; the wetness of the vegetation and underlying soil; and the density and height of the sward.

This general knowledge can be used to develop a framework, such as that of Mark Crick, for assessing the mapping potential of a habitat class by EO (Tables 1 and 2).

Table 1: The Crick Framework describing the options for mapping habitats as a tiered system (Source: Medcalf et al. 2011). VHR = Very High Resolution.

Tier					
Tier 1	Likely to be identified solely using EO				
Tier 2[1]	Likely to be identified using EO and ancillary data				
	Tier 2a - Likely to be identified using EO together with ancillary data	**Tier 2b** - Likely to be identified using VHR EO together with ancillary data	**Tier 2c**[2] - Likely to be identified using EO data (in some cases VHR) but ID dependent on good geological data	**Tier 2d** - Likely to be identified using EO methods such as fuzzy membership values	**Tier 2e** - Likely to be identified using EO including LiDAR to give detailed information about vegetation structure
Tier 3	Likely to be identified using EO and ancillary data but also dependant on availability of time series of imagery				
	Tier 3a - Likely to be identified using EO together with ancillary data	**Tier 3b**- Likely to be identified using VHR EO together with ancillary data	**Tier 3c** - Likely to be identified using EO data (in some cases VHR) but ID dependent on good geological data		
Tier 4	Currently unlikely to be determined using EO				
	Tier 4a - Habitats distinguished by low frequency or small features	**Tier 4b** - Habitat hidden from above for most of the year			
Tier 5	Cannot be identified using EO				

Table 2: The Crick Framework applied to 2 Nomenclatures: total number of classes detectable per mapping option (Source: Medcalf et al. 2011)

		UK BAP Priority Habitats	EC Habitats Directive Annex I habitats
Tier 1		0	0
Tier 2	2a	6	6
	2b	7	2
	2c	2	5
	2d	1	1
	2e	1	1
Tier 3	3a	6	5
	3b	9	11
	3c	4	6
Tier 4	4a	3	26
	4b	12	9
Tier 5		0	3
Total		51	75

A similar framework could be used to design a more ‘EO friendly’ habitat nomenclature. The work of Paradella et al. (1994) suggested that physiognomy may be the most important attribute which influences the EO response of vegetation. Jakubauskas et al. (2002), Moody and Johnson (2001) and Hill et al. (submitted) used time series of EO, exploiting differences in phenology to successfully map crop types, vegetation types or tree species.

The BioHab General Habitat Categories (GHC) classification system, adopted by EBONE for in-situ monitoring, is based on 21 or 34 plant life forms (Bunce et al. 2008), their % covers within a mapping element and a number of optional qualifiers (life form, environmental and management). The use of plant life forms enables the recording of habitats with comparable structures within contrasting bio-geographical zones. Based on the hypothesis that habitat structure is related to the environment, the GHC are also expected to correspond to phyto-sociological classes at high level. This makes the classification system not only applicable throughout the world, but also more amenable to EO’s sensitivity to vegetation physiognomy and cover. A set of EBONE test cases provide an insight into the EO mapping accuracies that could be achieved when using the GHC and further confirm the existence of a tier system as described in the Crick Framework (see section 2.3).

When continental or global consistency in EO methodology is imposed, the variety of EO data types and approaches available is greatly reduced. As a result, the current global, continental and national land cover maps produced from EO have been limited to reporting the extent of major vegetation types or ‘broad habitats’ at pixel sizes ranging from 1km to 25m with total number of vegetation classes ranges between 7 and 36 (Table 3). An investigation carried out by UNEP-WCMC found that although these land cover maps are a useful resource for indicating the distribution of broad habitats, they are inadequate for detailed biodiversity or habitat monitoring by land managers (Strand et al. 2007). The main reason is that the class number and type and the spatial detail of these products do not come anywhere near the thematic and spatial detail produced from a classification system such as the GHC (minimum mapping unit of 400m^2; total of 160 GHC with the average of classes found ranging substantially between zones), the UK BAP priority habitats (51 classes) or European Annex I habitats (75 classes).

Table 3: The spatial and thematic detail provided by the global, international and national land cover maps derived from Earth observation.

Land cover map	Pixel size or * MMU[1]	N^o Classes Total	N^o Classes Vegetation + Arable
IGBP (Loveland and Belward, 1997)	1 km	17	10+2
GLC2000 (Bartholome and Belward, 2005)	1 km	22	15+3
MOD12Q1 PFT (Friedl et al., 2002)	1 km	11	5+2
GLOBCOVER (Arino et al., 2005)	300 m	22	10+4
Land cover map of South America (Eva et al., 2004)	1km	31	21+4
CORINE Land Cover level 3, Europe	250,000 m^2 *	44	14+11
Vegetation cover map of India (Kumar Joshi et al., 2004)	188 m	35	20+2
USGS National land cover, US (USGS, 2010)	30 m	43	36+1
National Land Cover Database, US (Homer et al., 2007)	30 m	20	11+2
Land Cover map of UK (Fuller et al., 2005)	25 m	23	13+1
The Netherlands (Thunnissen and deWit, 2000)	25 m	39	19+9
GSD Land cover map, Sweden (Engberg, 2005)	25 m	57	na
Land Cover of Catalonia, Spain (http://www.creaf.uab.es/mcsc)	500 m^2 *	61	15+11

Reducing the spatial extent of a land cover map, is likely to enable more spatially and/or thematically detailed analysis, as relatively more resources can be made available for the task at hand (i.e. cost/km2).

One way of testing the suitability of the thematic and spatial information provided by EO derived land cover maps is through correspondence matrices (see D5.1) calculated from co-registering the in-situ habitat sample observations with the EO land cover map. Correspondence matrices are a standard method for assessing mapping accuracy. However, by assessing the clusters of one-to-one, one-to-many and many-to-many relationships within the matrix, this same information can be used to interpret patterns of correspondence or lack-off between in-situ habitat and EO land cover classes, helping to understand what makes certain EO derived land cover maps more suitable than others for integration with in-situ habitat observations. The preferred outcome would be a near perfect match which would show high correspondence values between individual or small groups of classes, shown as example A of the idealised correspondence tables (Figure 2). The worst case scenario is shown in example B, where there is no clear pattern of correspondence. The reality will be

[1] MMU: minimum mapping unit

somewhere in between (example C; Source: Deliverable 5.1) and will be function of a variety of factors:

- the strength of the match between the habitat class definitions implemented in the field and the EO-based habitat classes (i.e. the degree in which a relationship can be established between electromagnetic signals and the thematic classes identified in the field);
- mismatches introduced by a less than perfect spatial co-registration of the two layers;
- mismatches associated to differences in spatial scale between the two layers; and finally
- mismatches caused by an element of miss-classification in either or both of the layers (classification errors of EO imagery could be caused by, for example, the use of an unsuitable classification algorithm, or unsuitable or incomplete training sites).

Idealised correspondence tables

Example A:

	A	B	C	D	E
1	0	3826	0	0	0
2	0	4832	0	0	0
3	0	0	0	557	26
4	0	0	0	1195	752
5	0	0	7599	0	0
6	5328	0	0	0	0
7	0	0	445	0	0
8	667	0	0	0	0

Example B:

	A	B	C	D	E
1	630	630	630	630	630
2	630	630	630	630	630
3	630	630	630	630	630
4	630	630	630	630	630
5	630	630	630	630	630
6	630	630	630	630	630
7	630	630	630	630	630
8	630	630	630	630	630

Example C: correspondence table between in-situ habitat and EO land cover map layer for 1km2 sample

	Land Cover Map UK for 1km2 sample				
Broad Habitat (CS1998) for 1km2 sample	Dwarf Shrub Heath	Fen, Marsh, Swamp	Bog	Acid Grassland	Bracken
Bog (shrub)	57	15	87	13	57
Bog (grass/shrub)	31	79	0	20	4
Bog (grass/herb)	3	5	0	8	15
Inland Rock (Semi natural)	0	0	0	3	13
Coniferous Woodland	8	0	13	0	0
Acid Grassland	1	1	0	57	11

Figure 2: Tables demonstrating how correspondence can help reveal how well the class definitions and classification methods of two products (EO and in-situ) match up.

EBONE looked into this further by exploring the correspondence between the following in-situ and EO derived layers (Deliverable D5.1):

- the UK 2000 in-situ countryside survey samples (591 1km^2 in-situ samples) and the UK land cover map 2000 (25m grid cell resolution) both of which show the same habitat classes.
- the UK 2000 in-situ countryside survey samples (591 1km^2 in-situ samples) translated to GHC (Metzger et al, 2005) compared with the CORINE Land Cover 2000 classes (100m grid cell resolution).

The main findings were that fewer and more generic thematic classes result in higher correspondences, whilst increased discrepancies in spatial scale between in-situ and EO derived habitats maps (i.e. using a low spatial resolution and generalised EO map) will reduce the correspondences that can be achieved.

2.2. Introducing physical environmental variables

Physical environmental variables defining site conditions in detail (e.g. climate, topography, soil type and condition) can to some extent determine the types of habitats present. There is evidence that adding environmental variables to the classification of EO imagery improves accuracy and precision. For example, in the UK Land cover map, a soil map was used to separate spectrally similar grassland habitat classes. The USGS national cover map achieves 43 classes (Table 1) by introducing data on elevation and climate. EBONE achieved promising results when implementing a decision tree to predict the location of two Annex I habitat types across Europe using a combination of the existing EO derived European land cover map (CORINE land cover), altitude and soils data and a bioclimatic zonation (Annex-1). Still, the predictive power of environmental variables is expected to decrease where the landscape has had a long history of human intervention or land management. Also, the spatial detail and quality of the environmental data used will heavily influence the detail and quality of the ensuing habitat map. Currently, these spatially detailed (1-10m resolutions) environmental data often do not exist.

In the future, some of these environmental variables could become available. A recently launched satellite pair will soon (2014) deliver a 12 m global digital elevation model (http://www.infoterra.de/tandem-x_dem) from SAR data. Surface height models or elevation models, derived from airborne LiDAR data, are for an increasing number of countries, available at 1 to 5m resolutions. But other operational satellite EO products, such as, rainfall, relative soil moisture and land surface temperature are currently delivering at unsuitable spatial resolutions of 5 degrees, 0.5 degrees to 1km and 1km respectively. Technical bottlenecks need resolving before the acquisition of higher spatial resolution observations of such type of data will become possible. The alternative could be the use of regional land surface atmosphere interaction models to predict environmental variables such as soil moisture and land surface temperature. The quality and the spatial detail of their outputs are determined by (i) the quality and detail of the climate variables used to drive the models and (ii) the quality and suitability of the models. GEO-BON is taking the lead in developing Essential Biodiversity Variables which are required to track future changes in biodiversity. The definition of the EBVs should catalyze the efforts of the EO industry and academics to deliver data that is relevant and useful for monitoring biodiversity.

When available at coarser spatial resolutions, physical environmental variables can form the basis for environmental stratifications (WP3). As demonstrated by work carried out under the EU funded project BIOPRESS (Table 4), introducing such an environmental stratification greatly reduces the one to many relationships between EO Land Cover classes and in-situ habitat classes and so refines the thematic links between the two mapping systems.

Table 4: Example showing the importance of using an environmental classification to reduce the number of habitat classes in relation with an EO-based class: a global (Moss & Davies, 2002) versus regional approach for the CLC 3.2.2 'Moors and Heathland' and the corresponding EUNIS classes. The regional approach used quantitative correspondence data produced from Natura2000 sites located within BIOPRESS transect samples (See Biopress45 report). As a result not all EUNIS habitat classes that were linked to CLC 3.2.2 by Moss and Davies (2002) were found. Still, although not representative for the whole area of Europe it demonstrates the potential of a regional approach, (%) is percentage of quantified links (area correspondences), that are attributed to the EUNIS habitat type.

<table>
<tr><th colspan="2">EO-based Class</th><th>Corresponding EUNIS habitats</th></tr>
<tr><td colspan="2">CLC 3.2.2 without a regional approach (From Moss & Davies, 2002)</td><td>B1.5, B1.6, B2.5, B2.6, , B3.3, E5.3, F2.2, F2.3, F2.4, F3.1, F3.2, F4.1, F4.2, F4.3, F5.2, F5.4, F6.7, F6.8, F9.1, F9.2, F9.3, G5.6, G5.7</td></tr>
<tr><td rowspan="4">CLC 3.2.2
with a regional approach</td><td>Atlantic</td><td>F4.2 Wet heath (49%)
F7.4 Hedgehog heath (27%)
F2.2 Alpine and subalpine heath (11%)</td></tr>
<tr><td>Continental</td><td>F3.1 Temperate thicket and scrub (54%)
F2.2 Alpine and subalpine heath (18%)
F9.1 Riverine scrub (9%)</td></tr>
<tr><td>Alpine</td><td>F2.2 Alpine and subalpine heath (75%)
F2.3 Subalpine and oroboreal bush communities (10%)
F2.4 Pinus mugo scrub (9%)</td></tr>
<tr><td>Mediterranean</td><td>F5.1 Arborescent mattoral (36%)
F7.4 Hedgehog heath (31%)
Minor: F3.2 Mediterraneo-montane thickets, F2.2 Alpine and subalpine heath, F3.1 Temperate thicket and scrub , F6.7 Mediterranean gypsum scrub, F9.3 Southern riparian thickets.</td></tr>
</table>

2.3. EO mapping of GHC, summary of test cases

The test cases looked into five EO data options for mapping the GHC (Table 5).

- Lidar (Airborne; 26 - 0.45 pts /m2; digital elevation and surface height model, signal intensity derived from NIR signal; single date);
- Hyperspectral (Airborne; 5 m pixel; 127 bands covering the visible, NIR and SWIR; single date);
- Thematic Mapper (Satellite; 25 - 30 m pixel; 7 spectral bands covering the visible, NIR and SWIR; single date);
- Spot Image (Satellite; 10 m and 20 m pixel; 4 spectral bands covering visible, NIR and SWIR; single date);
- MODIS (Satellite; 0.25 – 1 km pixel; Vegetation index derived from visible and NIR spectrum; time-series).

Almost all test cases had a similar setup: the 1km^2 field samples, surveyed following the protocols described in the GHC handbook (D4.3), were used to train and validate the mapping success. Different EO data types were tested in different environmental zones. The choice of EO data was determined by the availability of the data to the EBONE team.

Table 5: overview of test case locations and EO data used

Country	MODIS series	TM	SPOT Image	Hyper-spectral	Lidar
The Netherlands		X		X	X
Estonia		X			X
Sweden			X		X
Slovakia	X				
Spain		X		X	
Europe	X				
Israel	X	X			X
South Africa			X		

Although the test cases do not represent a comprehensive assessment of all possible EO data for all possible landscapes and habitats, they provide a reasonable evaluation of how well certain EO data types could deliver the General Habitat Categories. The data types which are missing in this analysis are radar and thermal imagery.

LiDAR - airborne:

LiDAR (Light Detection and Ranging) is an active remote sensing system sending light pulses in the NIR. The time for the pulses to return back to the LiDAR sensor is used to calculate the distance to a target. The LiDAR sensor also records radiometric data, such as signal intensity, amplitude, and pulse angle. Airborne LiDAR data is generally available as a single date acquisition during winter or early spring, when the deciduous trees are leafless. Four test cases investigated the LiDAR's potential (Table 5 of Annex-2). The general consensus is that LiDAR will reliably separate LPH, MPH, TPH, FPH, and GPH of the 'trees and shrubs' GHCs (Table 6). As a matter of fact, using LiDAR produces more accurate estimates of height and of the % cover of height classes than those acquired through field surveying (Annex-2). The LiDAR height information was also shown to improve the GHC mapping accuracies achieved with multi-spectral imagery (Annex-3).

Table 6: The GHC under the heading 'Trees and Shrubs' are separated using height thresholds

DCH	SCH	LPH	MPH	TPH	FPH	GPH
Dwarf Chamaephytes, dwarf shrubs	Shrubby Chamaephytes, under shrubs	Low Phanerophytes, low shrubs	Mid Phanerophytes, mid shrubs	Tall Phanerophytes, tall shrubs	Forest Phanerophytes, trees	Mega Forest Phanerophytes, trees
<0.05m	**0.05-0.30m**	**0.30-0.60m**	**0.60-2.00m**	**2.00-5.00m**	**5.00-40.00m**	**>40.00m**

The vertical accuracy of current LiDAR systems varies with ground surface condition and canopy density but is generally below 10 cm (Annex-4), so relying on LiDAR to identify and separating life forms with height ranges around and below 10 cm (i.e. DCH and SCH) is not advisable.

Further separation of the TRS GHC based on their qualifiers DEC, EVR, CON, NLE, SUM was not tested. Separating DEC, EVR and SUM should be possible with multi-spectral imagery provided the timing of the EO data was chosen correctly or multi-date imagery was used (Boyd and Danson, 2005). Identifying CON and NLE may prove more difficult (Yang et al., 2007).

One area not evaluated by EBONE but demonstrated in other studies, is the use of LiDAR to deliver indicators of vegetation structure and woody habitat condition which have been successfully used to predict bird species richness in grasslands and forests (see review in Annex-2).

Hyperspectral – Airborne (Annex-5):

Hyperspectral sensors are passive systems which record the surface reflectance in continuous and very narrow spectral bands (~3 a 18 nm) across the visible, near- and mid-infrared spectrum (from ~ 450 nm to ~2400 nm). Hyperspectral observations make it possible to detect most of the absorption features found in the spectra of vegetation (Ustin et al. 2004). This is in contrast to multi-spectral observations (for example, Thematic Mapper or MODIS, Spot Image) where a limited number of discrete spectral bands are recorded, focussing around main absorption features.

The HyMap (Hyperspectral Mapper) airborne sensor used in the EBONE test cases (The Netherlands and Spain) recorded reflectances in 126 spectral bands from 450 nm to 2480 nm at a spatial resolution of 5 m. The standard method for using hyperspectral data is to use spectral signature matching procedures using typical reflectance spectra of the 'pure end-member' to determine the composition of both homogeneous or heterogeneous (i.e. mixed) pixels. Hyperspectral imagery is particularly suited for an end-member based classification as the many narrow spectral bands increase the likelyhood of finding features in the spectral

signature which are unique to the end-members of interest which in the case of EBONE are the life forms defining the GHCs.
The manner in which the GHCs are being mapped, i.e. parcels are being assigned % coverages of life forms, makes the GHC nomenclature potentially very suitable for end-member classifications and spectral unmixing approaches. The critical requirement is that the plant life forms present in the mapping area (maximum 34, but generally fewer) have distinct spectra. Experimental and modeling studies (Gates et al.,1965; Thomas et al., 1971; Ross, 1981; Goel, 1988; Myneni et al., 1989; Wessman, 1990; Walter-Shea and Norman, 1991; Curran et al., 1992; Jacquemoud et al., 1992, Gitelson and Merzlyak 1997, Peñuelas et al. 1997, Asner et al., 1998) have amply demonstrated that vegetation reflectance is mainly a function of tissue optical properties (leaf, woody stem, and standing litter), canopy structure (e.g., leaf and stem area, leaf and stem orientation, and clumping), soil reflectance and viewing geometry, where the tissue optical properties are function of biochemicals, water content and intra-cellular structure and soil reflectance is function of soil moisture, roughness and texture, organic matter content, and mineralogical composition. Figure 3 shows the outcome of a study by Asner (1998), evaluating the contribution of each of these factors relative to all the other factors for a series of grassland, shrubland, and woodland sites in Colorado, New Mexico, Texas and the Cerrado region of Brazil. It shows that most of the reflectance variability is explained by one or two dominant factors and that these vary with cover type. The potential for a successful GHC life form separation using reflectance values will depend on whether the life form definition includes traits (e.g. vegetation height, leaf area, leaf clumping) which are directly or indirectly related to the most contributing factors.

The review by Ustin et al (2004) highlights the unique value of airborne hyperspectral data. Its capability of detecting very narrow absorption bands which are indicative of, for example, canopy water content and specific canopy biochemicals enables it to be used for a wide range of applications at local level, including detailed habitat and vegetation species mapping. However it is clear from the examples provided that what is achievable is very much specific to the site and its conditions.

The conclusions from the EBONE test case in The Netherlands confirms the above (Annex-5). The success of the GHC classification is dependent on the life forms being spectrally distinct and their spectral signature ranges (variance) showing low overlap. Overall site mapping successes achieved ranged from 64% to 78%. The accuracies achieved for specific life forms varied substantially. Better classification results could be obtained by combining hyperspectral imagery with LiDAR data which would deliver the height based life forms at high accuracy. Because of the manner in which the GHC classes are defined, achieving a GHC map requires, depending on the spatial resolution of the imagery, either the unmixing of image pixels to % coverages of life forms, or imposed parcel outlines for which % coverages of life forms are calculated and translated to GHC. In the latter case, determining the parcel boundaries will have to be the first step to classification. This aspect is discussed further under heading 4.

The conclusions from the EBONE test case in Spain mainly highlighted the importance of increasing the spatial detail whilst maintaining the spectral range: the 4 m airborne HyMap imagery delivered more spatially detailed and consequently thematically more accurate (evaluated visually) GHC maps than the 30m Thematic Mapper image.

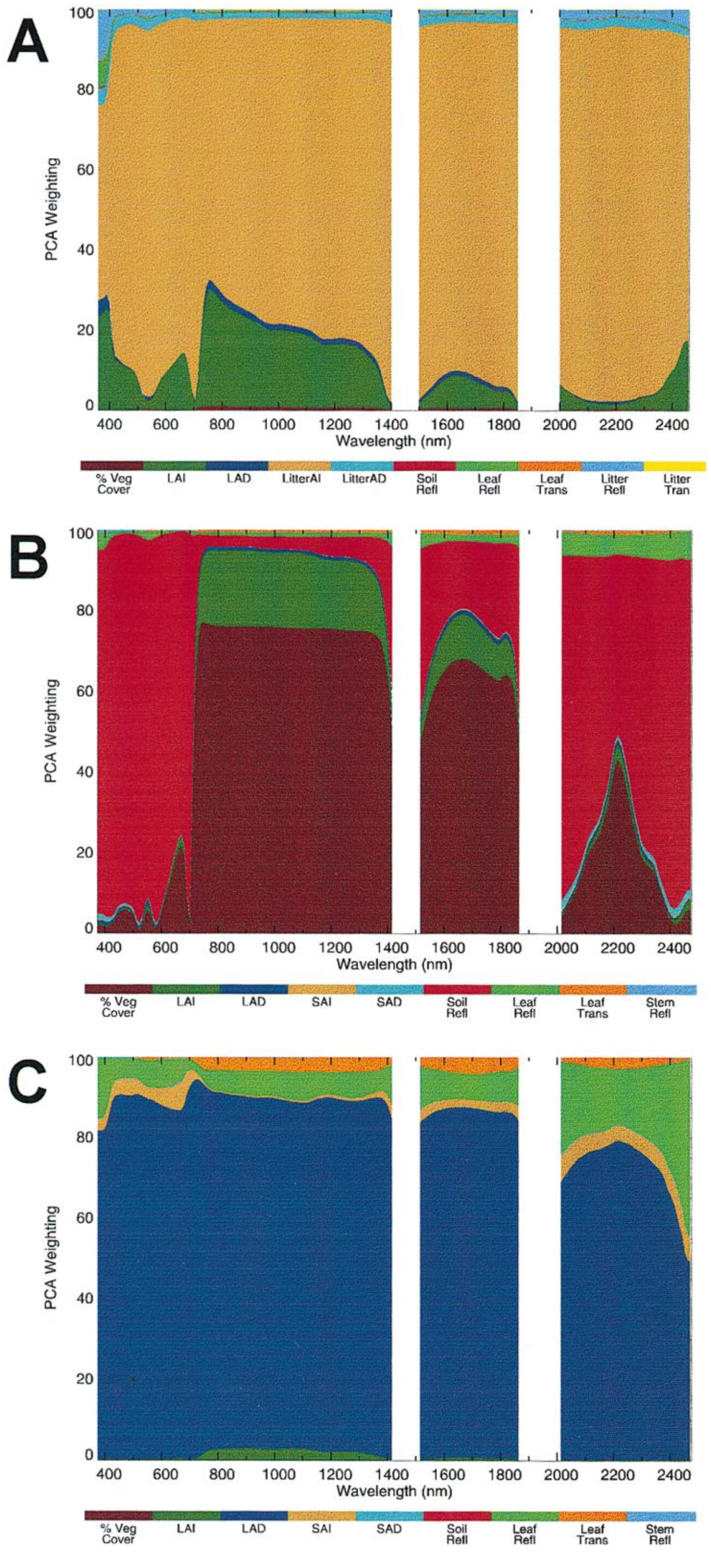

Figure 3: Diagram showing the relative contribution of the main structural vegetation parameters to the variability in reflectance across the spectrum of a hyperspectral sensor for a grassland (A), shrubland (B) and woodland(C) site. (Source : Asner 1998). LAD = leaf angle distribution; LAI = Leaf area index; LitterAD= litter angle distribution; LitterAI = litter area index; SAD= Woody stem angle distribution; SAI= Woody stem area index; leaf litter and stem reflectance and transmittance are determined by their optical and biochemical properties.

Thematic Mapper – Satellite (Annex-6, 7and 8)

The Thematic Mapper, and variants (e.g. SPOT-image; Linear Imaging Self-scanning Sensor – LISS; Advanced Spaceborne Thermal Emission and Reflection Radiometer – ASTER; and the planned sensor on Sentinel-2) are satellite borne passive sensors which record the surface reflectance in 4 a 7 discrete and broad spectral bands (~ 300 a 1000 nm) across the visible, near- and mid-infrared spectrum (from ~ 450 nm to ~2600 nm) at a spatial resolution ranging from 10m to 30m. It is widely known that multi-spectral information will separate vegetated from non-vegetated areas. This data is also generally good at differentiating coniferous from broadleaved vegetation and arable and grasslands from woody vegetation provided the timing of the EO data is such that it enhances the spectral differences. Many national and continental land cover maps are based on this type of imagery (e.g. US, The Netherlands, Sweden, UK, Europe - see Table 1). The capability of delivering the GHC was tested through test cases in Estonia, Spain and Israel.

The general conclusion is that this type of imagery contains many mixed pixels which impacts on the mapping accuracies especially when the landscape is complex and hetergeneous. Pan-sharpening the TM imagery with higher spatial resolution imagery helps resolve this problem to some extend (e.g. Spain and Israel). In the case of Estonia where the test sites were located in an arable landscape with many large fields the accuracies achieved varied from 75% to almost 100% (Annex-6). For the Mediterranean sites in Israel the overall classification accuracies were between 30% and 60%, after merging some of the GHC classes. Among classes, trees (including maquis) were mapped well (accuracies between 60% and 90%), whereas the success in mapping the shrubs and herbaceous classes was lower (Annex-8). The classifications of the test sites in Spain delivered disappointingly low correspondences with the in-situ data (no quantitative data available) (Annex-7). For both Spain and Israel it was clear that the classification success was dependent on the timing of the image acquisition coinciding with the dry or rainy season.

MODIS – Satellite (deliverable D5.2, Annex-2):

MODIS, and variants (SPOT VEGETATION, MERIS, AVHRR) are satellite borne passive sensors which revisit the same spot every day and record the surface reflectance in discrete and broad spectral bands (~ 300 a 1000 nm) across the visible, near- and mid-infrared spectrum (from ~ 450 nm to ~2600 nm) at a spatial resolution ranging from 250m to 1000m. Their main feature is the provision of time-series of daily vegetation indices data which opens up the potential to exploit the information to capture habitat leaf phenology (Figure 4). The main disadvantage of such data is the reduced spatial resolution which means that often a single pixel represents a mixture of land cover.

Four EBONE test cases investigated the use of time-series of data. The first case focussed on grassland GHCs in Slovakia, the second on forest GHCs in Austria and Slovakia, the third on two Annex I habitats and the final on Israel in general. Both the forest, grassland and Annex I habitat test cases found that the variability in phenology behaviour between and within GHC classes is too great to enable an effective separation of classes using phenometrices (i.e. metrices describing the phenological signal such as growing season length and amplitude). The spatial scale of the observations (250m – 1km), which results in many mixed pixels, is one of the confounding factors. The other factor is that phenology is only a secondary attribute in the GHC classification system, as illustrated by Figure 5 (Annex-8). Still, the grassland case study demonstrated the value of phenology information for separating grassland types and monitoring their condition, provided that the location of the grasslands is known a priori. Increasing the spatial resolution of time-series of vegetation indices to match the spatial scale of grassland or woodland patches would substantially reduce the occurrence of mixed pixels and bring about this potential.

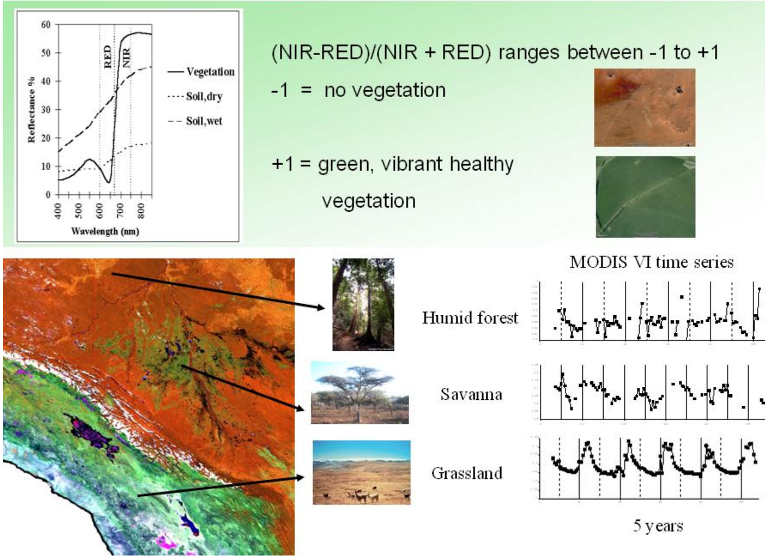

Figure 4: Schematic illustrating how time-series of vegetation indices (VI) can capture vegetation leaf phenology. The example 1200km x 1200km MODIS image (left) shows the Altiplano grasslands, lowland savannas and tropical forests of parts of Bolivia and Peru.

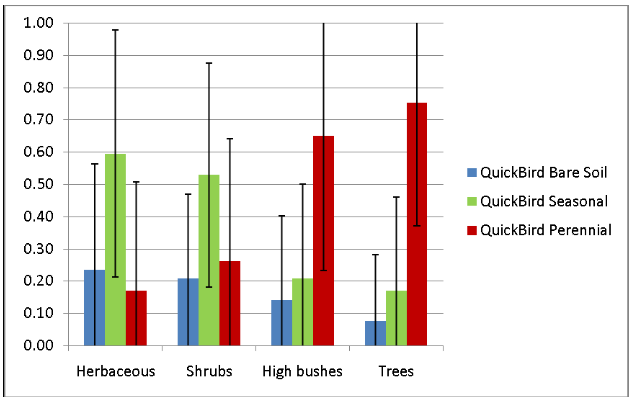

Figure 5: Representation of percent coverage of phenology classes (bare soil, seasonal and perennial vegetation) for each of the four combined EBONE GHC categories in Ramat Ha'Nadiv, Israel (herbaceous, shrubs, high bushes, and trees) (Source: Annex-8).

2.4. Landscape complexity

When the EO mapping performance of habitats is assessed and the spectral detectability of a particular habitat is discussed, the environmental context of the study area is often only briefly mentioned. Nevertheless, it is important to understand how the spectral properties of the area surrounding a habitat influence the detectability of that habitat. Andrew and Ustin (2008) suggest that EO mapping successes are influenced by site complexity. This was tested as part of the HyMap case study in The Netherlands (Annex-5). The general finding was that mapping success decreases with an increase in Biological Complexity. The EBONE test case involved 4 sites so the results are indicative only. The work of Andrew and Ustin (2008) also demonstrated an inverse relationship between the Spectral Complexity and mapping success.

High spatial resolution (centimeter to meter resolution) can result in high within patch spectral variability which, as is the case in the work of Andrew and Ustin (2008), can be treated as a source of mapping error. Others, however, have used it as a source of information and have suggested that, spectral complexity could be linked to biodiversity. It is based on the spectral variation hypothesis, i.e., spatial variation, expressed as a standard deviation of reflectance, is likely to be correlated with spatial variation of the environment, which in turn is likely to be correlated with plant species richness (Palmer et al. 2002). Oldeland et al. (2010) tested this hypothesis in a savanna ecosystem with positive results, while Schmidtein and Sassin (2004), working in Alpine meadows, found that although heterogeneous reflectances were always a sign of heterogeneous species composition, homogeneous reflectances did not always indicate a homogeneous plant species composition. In the tropics Asner et al. (2011) have developed the concept of spectranomics where spectral diversity can be linked to the chemical diversity of the tropical forest canopy which in turn can be linked to plant trait diversity. Considerable uncertainty remains about the utility of these approaches for biodiversity monitoring, and, given its potential for this, further research is needed to determine the main factors that contribute to spectral heterogeneity.

3. Habitat extent- Methods for integrating in-situ and EO

Using a strict interpretation, the idea of integrating in-situ with EO data is that the combination of the two data set types will deliver information which is more accurate or precise than either of the two data sets used independently. A more relaxed interpretation of integration is the use of one type of data to improve the accuracy or precision of the information of the other data, or alternatively to make the collection of the other data more efficient.

We considered the following options where the EO and in-situ play different roles:

- using in-situ samples to re-calibrate a habitat map independently derived from EO; this is referred to as 'inter-calibration';
- using an independent but less accurate EO layer characterising the general spatial variability in cover to post-stratify the in-situ samples;
- using in-situ samples to train the classification of EO data into habitat types where the EO data delivers full coverage or a larger number of samples.

3.1. Inter-calibration of EO and in-situ monitoring

Inter-calibration refers to an integration approach developed for the UK (Fuller et al. 1998; Hill and Smith 2004). Inter-calibration uses correspondence matrices (Lillesand and Kiefer, 1994) that are created to calculate the classification accuracy of EO derived land cover maps. For each 1km square Countryside survey 2000 field data (CS2000) a correspondence matrix was produced with the land cover map 2000 (LCM2000). Correspondence matrices were averaged within strata (the ITE Land Classes) to produce stratum specific calibration matrices. These calibration matrices are then used to adjust the stock estimates per 1km square produced by LCM2000 for each stratum (Figure 6). Although this approaches reduced the original spatial resolution of the land cover map from 25 m to 1 km, Fuller et al (1998) and Hill and Smith (2004) found that, at national level, the habitat statistics produced from the calibrated land cover map closely matched those extrapolated from the field samples. Confidence intervals for adjusted stock were produced using a Monte-Carlo bootstrapping procedure and it was concluded in Fuller et al (1998) that in most cases the calibrated results produced more precise stock estimates than either the LCM2000 or CS2000 alone. However, a closer assessment of the publication and report showed no clear evidence that the revised stock estimates were closer to the truth. Moreover, the report inter-calibration increased the uncertainty of national stock for 16 of 19 land cover types. In their own conclusions Hill and Smith (2004) did acknowledge that their work posed more questions than answers. They identified weaknesses in both the FS and EO approaches to stock estimation and made 9 recommendations about how to conduct future surveys, so that the integration of FS and EO approaches could lead to improved estimates of stock. The main points have been condensed to a shorter list below:

- Timing of surveys: Due to the dynamic nature of some of the habitats (for example agricultural and coastal) the time difference between products should be minimised.
- Spatial resolution of products: The minimal mappable units (MMUs) of products should be normalised (most likely to the largest) prior to any correspondence analysis to prevent features that could not exist at the coarser MMU being seen as error.
- Thematic differences: Thematic differences between products should be avoided.
- Rarity: Rarity and patch structure should be considering. Classes with limited extent compared to the largest MMU should be avoided.
- Knowledge Base Enhancements and Validation: The use of additional spatial data is necessary in order to disable calibrations that worsen the results and also for validation. Care should be taken to select datasets with suitable thematic and spatial specifications, temporal similarity and appropriate uncertainty information.

It is worth noting that the work of Hill and Smith was delivered as a contract report and was never subjected to peer review. Inter-calibration was not tested in EBONE. Future work should consider evaluating this option rigorously.

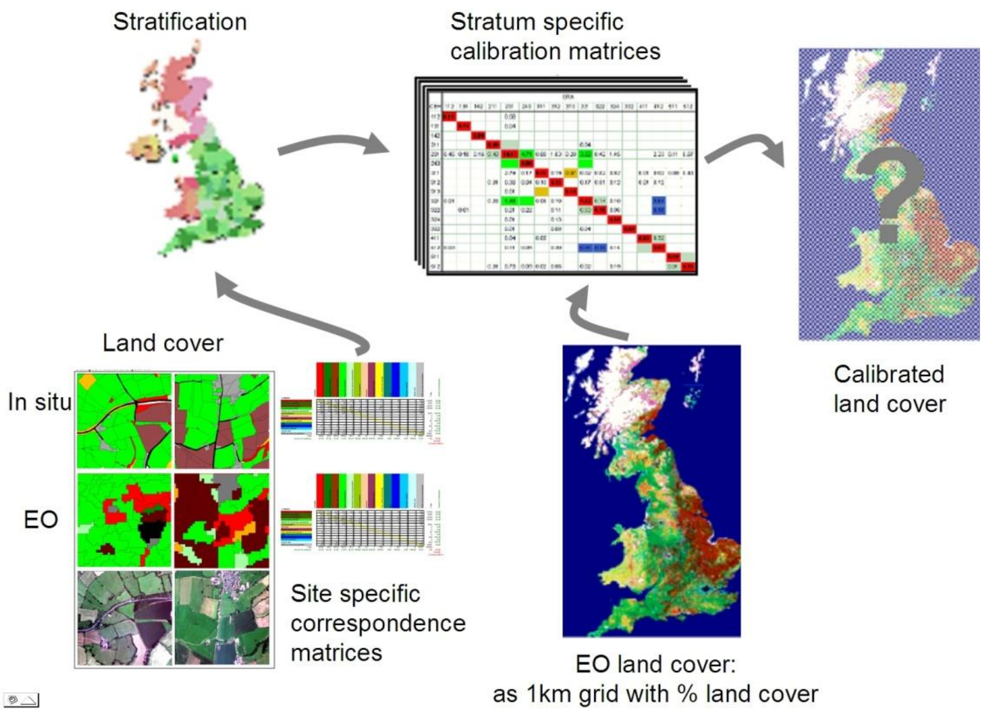

Figure 6: Diagram illustrating inter-calibration as implemented by Fuller et al (1998)

3.2. Post stratification (Deliverable 5.4)

When only statistics and not wall-to-wall maps describing the spatial pattern of different habitats or categories are needed, the combined use of EO data and data from sample-based inventories can provide accurate area estimates for various categories. Almost unbiased area estimates of habitats or classes can, for example, be obtained by combining EO data and *in-situ* data using post-stratification. Previous work has shown that post-stratification, where satellite images or classified satellite images are used for stratifying existing sample based forest inventories, improves the accuracy of estimated forest characteristics (McRoberts et. al., 2002 and 2006; Nilsson et al., 2003 and 2009). Similarly, CORINE land cover data was used to post-stratify in-situ data from the LUCAS sample based land inventory to improve the accuracy of area estimates for various coastal land cover classes (Galego and Bamps, 2008).

EBONE tested this approach for one of the nine environmental strata of Sweden combining the comprehensive NILS inventory data (NILS; http://nils.slu.se/) with the EO derived Swedish GSD land cover map (Engberg, 2005). The results obtained in this study also show an increase in precision when using classified satellite images for post-stratification, further confirming that post-stratification is an easy and straight forward method that can be used to derive improved area statistics for habitats. One important advantage of using products like the GSD Land Cover map or the CLC2000 map for the stratification is that they already exist. The increase in precision obtained using post-stratification also means that estimates of the area covered by different habitat classes can be presented for smaller areas than possible from estimates based on a sparse sample of *in-situ* data alone, without any reduction in precision.

An important future research task is to test if the use of other EO derived map products can improve the estimation accuracy for selected habitats and whether similar results can be achieved in other landscapes (e.g. Mediterranean). It will also be of interest to investigate how the gain in efficiency for post-stratified estimates (RE) is affected by the number of *in-situ* observations used.

3.3. Training the classification of EO imagery using in-situ samples

The most relaxed definition for integration is to use the in-situ field samples to train and validate the classification of the EO data into habitat types. The EO data could either deliver full coverage or a larger number of samples.

Traditionally, the collection of training data for any EO classification algorithm would focus on identifying spectrally homogeneous areas of the cover classes of interest, ensuring that the within and between class spectral variability is represented. To avoid unclassified areas in the imagery it is important to ensure that the full range of spectral signatures found in the imagery have been identified and allocated to a cover class. Unsupervised image classifications are often used as a tool to explore the spectral information content of an image and help guide the field work. Field work is organised to capture and confirm the cover identity of the spectral classes observed on the imagery as effectively as possible. A sampling strategy designed to train and validate an image classification will not only have to take into account the spatial distribution of the cover classes of interest, but also the within class spectral variability found across the imagery. Consequently a sampling strategy designed for EO image training, classification and validation is unlikely to suit the purpose of delivering unbiased and precise estimates of habitat extend and vice versa. The EBONE team investigated this when assessing the use of TM imagery in Estonia (Annex-6) and Spain (Annex-7) and found that *'Single central monitoring square can be non-representative for surrounding squares'*; *'Supervised classifications of satellite imagery are only possible when targeted training samples have been collected in the field'*; and '*unsupervised image classification was useful to examine the spectral variation in the image, within field mapped GHC areas and to locate those areas for which the supervised classifier did not have a like training area in the monitoring square.'*

3.4. Sampling strategies (Deliverable 5.4)

'Going in-situ' is the only way to collect detailed information on the flora and fauna present. Also in-situ land cover or habitat observations, when benefiting from a well designed field survey approach and protocol, have the advantage of providing high thematic and spatial detail. In-situ work is intensive and costly and is therefore limited in the area it can cover and the revisit frequency. One question EBONE looked at, using a statistical simulation experiment, was whether using EO to increase the number of samples to increase precision, is a viable option. This option only makes sense if EO can be made to deliver local habitat maps at an acceptable accuracy using a variety of more expensive and sophisticated EO data (high spatial, spectral and temporal resolution imagery, Lidar), an option which would be a very expensive proposition if acquired at national or continental scale to deliver a wall to wall coverage, but potentially cheaper than field work if limited to sample areas.

The take home messages from this work are that:

- the effect that EO sample has on precision or bias will depend crucially on differences in user (omission) and producer (commission) accuracy (WP8 provides further details about the statistical procedure to estimate precision and bias);
- unbiased estimates are obtained when user accuracy (omission) = producer accuracy (commission);
- it is possible to correct for possible systematic bias if and only if the EO sample and the in-situ sample partly overlap so that user and producer accuracy can be estimated. This overlap, however, should be sufficiently large to ensure that user and producer accuracy themselves can be estimated precisely and without bias. In this respect, it is also crucial that the overlapping part of both samples is a spatially balanced, random sample to avoid bias.

The figures 7 and 8 below (Source D5.4) illustrate how the bias and precision of habitat area estimates are affected by the habitat mapping (producers and users) accuracy achieved with EO.

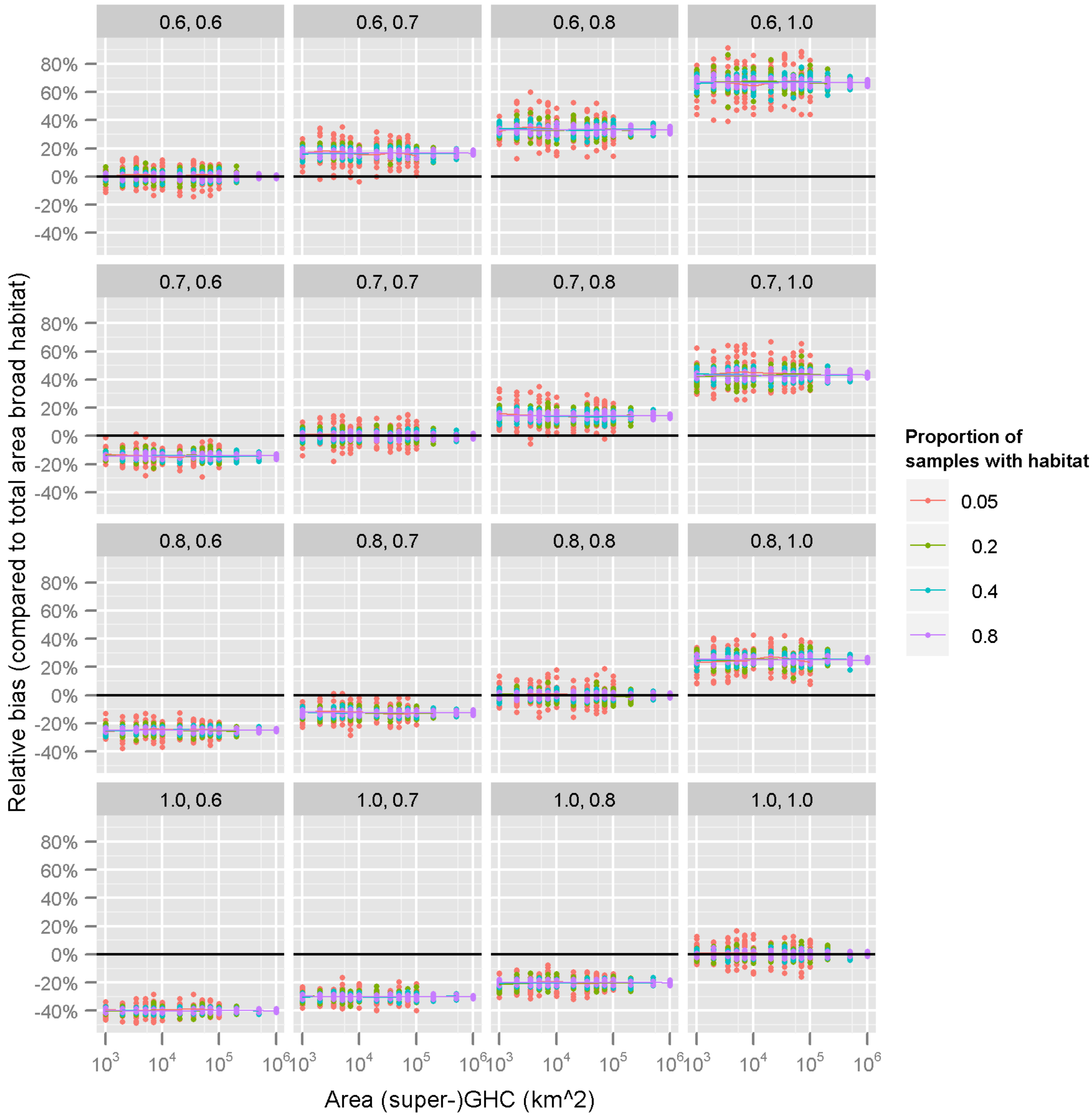

Figure 7: Relative bias as a function of user and producer accuracy. The heading above each panel gives user accuracy and producer accuracy respectively. The lower right panel corresponds with the situation where in-situ samples and earth observation samples give identical results (i.e. 100% accuracy; for comparison purposes only). The sample size is equal to 10000.

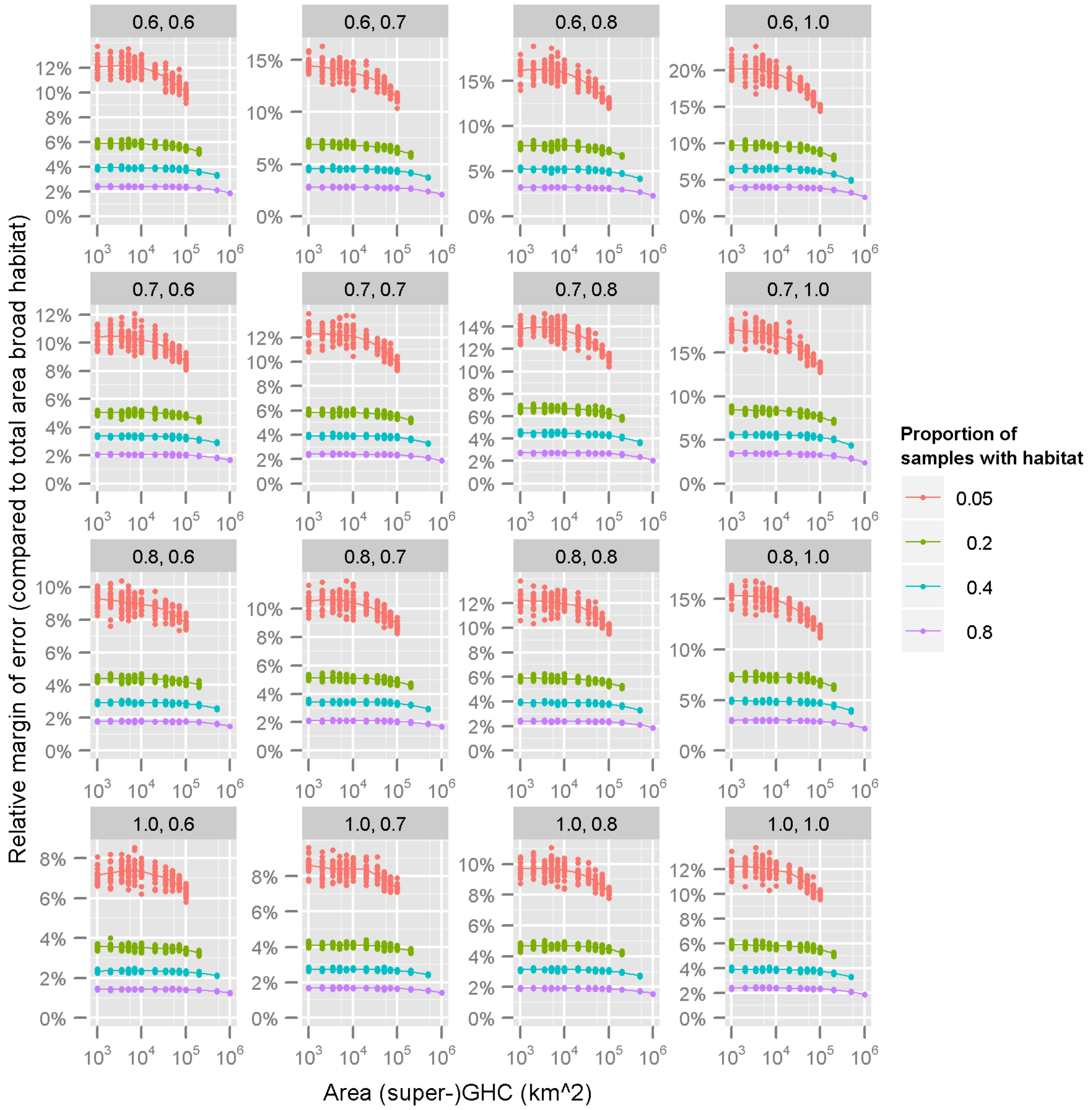

Figure 8: Relative margin of error as a function of user and producer accuracy. The heading above each panel gives user accuracy and producer accuracy respectively. The lower right panel corresponds with the situation where in-situ samples and earth observation samples give identical results (i.e. 100% accuracy; for comparison purposes only). Sample size used was 10000.

When exploring for a cost-effective monitoring design, the problem that needs solving is how to achieve a good balance between the output quality of the design and the available monetary budget (or alternatively, the constraint could be formulated in terms of time).The effectiveness can often be related to statistical concepts, such as the margin of error or the sampling variance. Which measure for effectiveness will be most useful will depend on the question at hand. For estimation of a mean or a total, higher effectiveness is related to a narrower confidence interval. For trend detection, the effectiveness will depend on the power to detect a trend, and so this will depend on the magnitude of the trend that needs to be detected. For a given sample size, we can thus assess effectiveness.

Establishing relative differences in cost between in-situ sampling and EO is the other essential ingredient. However, although estimates of the cost associated with field work were available (through the EBONE pilot studies) those associated with the EO work were lacking. This situation is not uncommon and for it to improve it is important that we all actively encourage the documentation and reporting of costs associated to EO mapping activities and field work.

4. Habitat extent- EO in support of the field work

The GHC system is based on determining the composition of individual plant life forms for habitat mapping units with a minimum area of 400 m^2. In the field, the identification of these habitat mapping units is a major challenge especially when the transitions between mapping units are gradual. BIOHAB's protocol strongly recommends the use aerial photography to identify and manually digitise habitat mapping units which can then be subsequently labelled in the field (Figure 9). This approach reduces the time spent in the field and ensures a more accurate spatial delineation of the habitat units. Forest managers and nature conservation agencies are well aware of the value of aerial photography and have for some time now fully incorporated aerial photo interpretation into their operational field surveying activities (for example, UK Country Side Survey (Barr et al., 1993)).

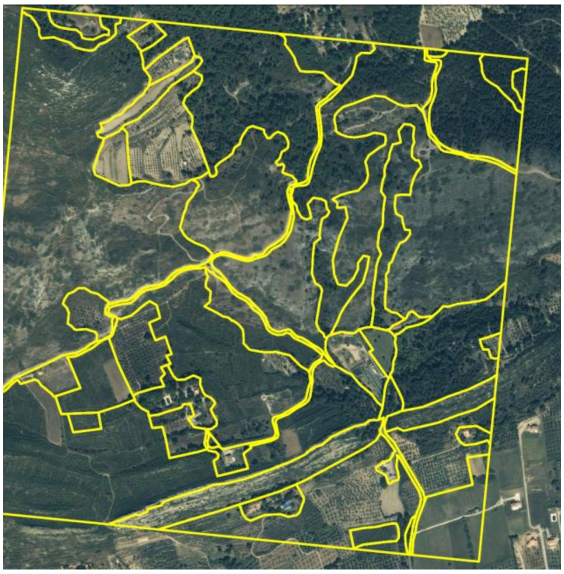

Figure 9: Example of the manual digitisation of an aerial photo for a 1km2 sample prior to the field survey.

Manual digitisation benefits from the human ability to recognise spatial patterns and, in some cases, the local knowledge of the interpreter. The main disadvantage is the subjective nature of manual interpretation which impacts on the consistency of the interpretation in space and time. Steps can be taken to reduce this impact, such as, provide clear and complete interpretation rules which have been thoroughly tried and tested; train and regularly re-train the interpreters and; use people who are familiar with the local or regional landscape. Still quantifying consistency remains difficult and manual digitisation takes time.

The general consensus among the EBONE team was that automated image segmentation of the aerial photographs would reduce the time spent digitising mapping units and ensure consistency. This was not tested within the project. Image segmentation is the process of partitioning a digital image into parcels or segments which contain neighbouring pixels that are similar in terms of reflectance value (colour, intensity) or texture. The main potential problem with image segmentation is that the underlying algorithms require user defined input parameters which prescribe 'when to stop adding to or growing the segment' and subsequently determine the number and size of the resulting segments. Optimising these input parameters is an iterative and interactive process which will be partly function of the landscape. Figure 10, taken from Gerard et al. (2003) illustrates this issue, showing how the choice of 2 input parameters can drastically change the number (and size) of resulting segments.

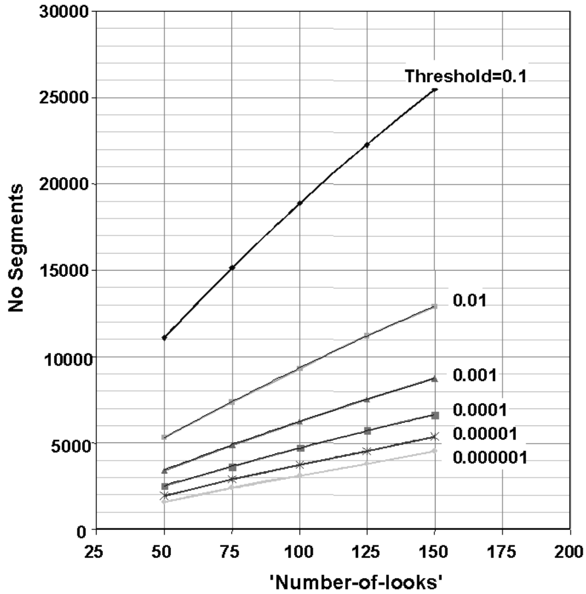

Figure 10: Variation in number of segments produced for a 700 km x 700 km area from a 1 km resolution NDSWIR SPOT-VEGETATION image by the CAESAR MUM image segmentation procedure as a function of the input parameters “threshold” and “number of looks.” (Source: Gerard et al 2003).

Nevertheless the advantage of being able to quickly produce digitisations based on relatively consistent clustering rules which are repeatable and easy to document, are likely to outweigh this problem. Another advantage is that such an approach can easily be implemented on multiple layers of imagery, enabling a segmentation based on a combination of, for example, spectral reflectance, height information and image texture. Figure 11 shows the results of a small EBONE study that explored how the segmentation of combined LiDAR and aerial photography could be used to deliver habitat mapping units for field surveying (see Annex-3). The potential of image segmentation is clearly demonstrated, however a more thorough study involving a range of test cases which represent a variety of landscape types is required to establish if image segmentation is not only more cost effective but also more consistent and precise than manual interpretation.

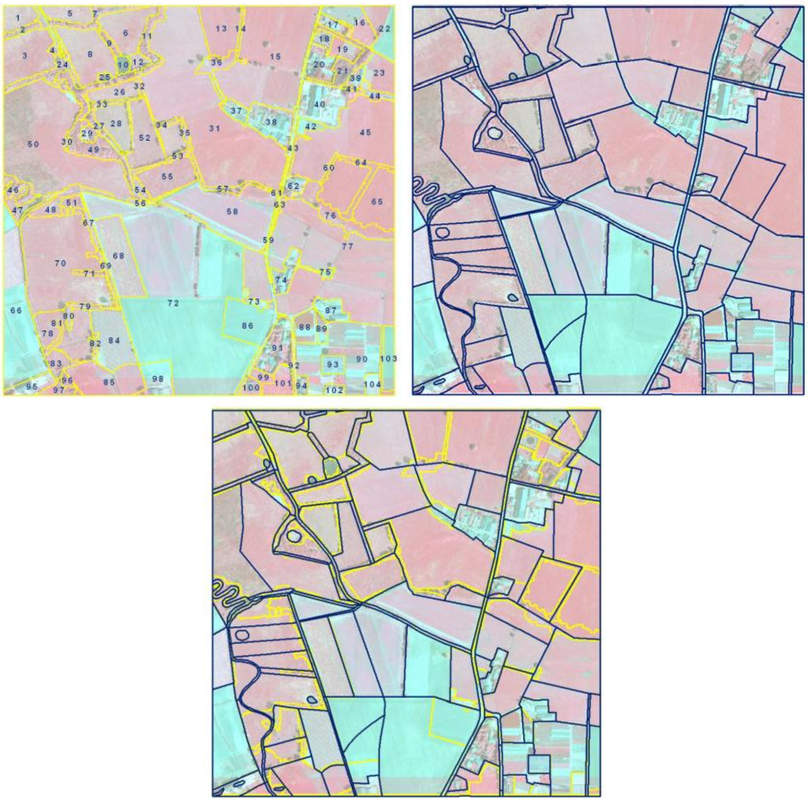

Figure 11: The habitat mapping units created through (a) segmentation of combined Lidar and aerial photo data; (b) manual interpretation of the aerial photo and (c) an overlay of both approaches (from Annex-3).

5. Habitat - pattern related measures (Deliverable D5.3)

Landscape ecology is based on the premise that there are strong links between patterns, functions and processes and a number of studies have explored the utility of spatial metrics in landscape analysis since the 1980s. As a result, the number of pattern related indices has proliferated. Nowadays, the potential (non-expert) user, either from landscape planning or environmental local, regional or national agencies or from international agencies, who is looking for one measure of pattern, is left alone in front of this plethora of indices. The test case in EBONE was an attempt to respond to this need of guidelines and standardization to measure pattern. It also investigated how to deliver pattern measures which provide context for the in-situ field observations.

The EBONE test case focussed on the customisation, integration and automation of available and well selected pattern models. Its final aim was to derive a system of standardised ecologically meaningful characterisation of pattern.

The example GHC of interest was arbitrarily decided to be forest phanerophyte. The three models considered (GUIDOS/MSPA, Landscape mosaic and connectivity models) were revisited to present new indices characterising morphology, interface mosaic context and connectivity. User information requirements were assumed to be about

- the landscape share of anthropogenic versus more natural habitats;
- the availability of interior habitat and connecting linear features;
- the presence of isolated features;
- the mosaic interface context at edges; and
- the habitat connectivity at landscape level.

The models were successfully applied to the available EO based land cover maps and the sixty 1km ^{2} field samples available in the EBONE project. The samples represented areas in France, Austria and Sweden. Each field sample was easily and quickly characterised in a standardised manner for the forest GHC. The methods could easily be applied to other focal GHC provided that the habitat is accurately identify in the field and using EO. The sample based results showed a high level of within stratum variability across all three types of indices (morphology, interface mosaic context and connectivity).

Due to insufficient sample size (1km2) and sample population for certain environmental zones, a proper multi-scale and multi-source data assessment could not be done and only an illustration of the scale dependency of the results was provided over few samples (Figure12). Connectivity analyses were implemented using 25km x 25km analysis units providing macro-connectivity information context to the available habitat samples, which in turn were characterized by their micro-connectivity level.

Quantifying spatial pattern is not an end in itself, rather it should be the first step to understanding ecological processes. Spatial pattern analysis is of limited value if not used to explain structural changes in landscapes and predict how they influence ecological processes (Li and Wu, 2004). The spatial and temporal dimensions as well as field recording of ecological condition of habitats should be integrated in monitoring programs to increase our understanding of pattern-process relationship. This standardised pattern characterisation will probably facilitate such studies (which are too often restricted to basic patch area measures such as in Krauss et al, 2010) and the comparison of pattern processes across regions.

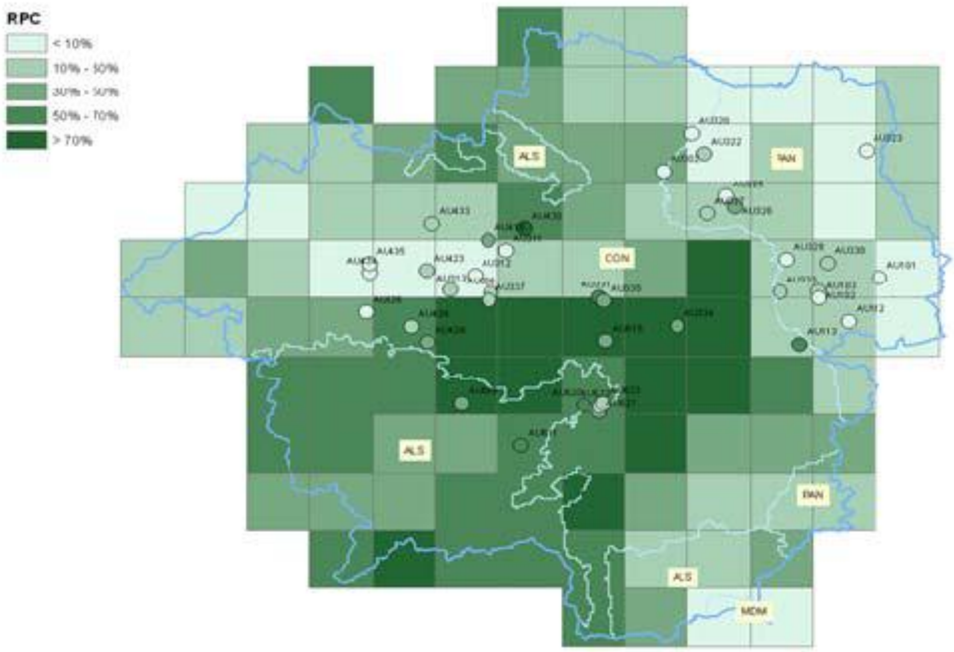

Figure 12. Macro and micro connectivity information (RPC) in Austria case study. Macro-connectivity is derived from the analysis of 25km x 25km units. Micro-connectivity is available for each 1km^{2} sample (circles shade according to their RPC values)

6. Conclusions and recommendations

A measure of the biodiversity indicator 'Habitat extent' could be delivered in two formats: as sample-based estimates for a region, country or zone or as a wall to wall map showing the distribution and extent of the habitats. In-situ observations will deliver the former whilst EO based observations are expected to deliver the latter. General expectations are that a combination of the traditional in-situ surveys and EO-derived land cover/habitat products could deliver better maps and/or estimates more efficiently.

When considering wall to wall habitat mapping, it has become clear that, at the moment, even with the various types of EO data and EO mapping techniques currently available, the level of thematic and spatial detail required for habitat and biodiversity monitoring cannot be achieved for all the habitat types of interest. When considering EO, one should always bare in mind that the quality and detail achieved when mapping land cover or habitats using EO is primarily limited by the manner in which the electromagnetic radiation interacts with the physical and chemical properties of the land surface and the manner in which the electromagnetic radiation is being recorded (spatial resolution, spectral range and resolution, temporal resolution, active or passive system).

The EO mapping success of habitats varies with landscape and habitat type, so although a wall to wall coverage showing the distribution of all habitat types of interest may not be possible, EO can produce good quality distribution maps of selected habitats. Adopting an EO based perspective of habitats (e.g. Crick Framework) to predict the EO mapping success of the habitat classes at the start of a mapping project, would not only help direct the effort towards the mappable habitats but also help manage stakeholder expectations.

Introducing physical environmental variables to improve EO mapping success is widely accepted as the way forward. However, a thorough review to establish in which circumstances the added environmental information is likely to make a significant difference is still required.

When considering the combination of the traditional in-situ surveys and EO-derived land cover/habitat products, a couple of potential options were identified.

One option was using in-situ samples to re-calibrate a habitat map independently derived from EO ('inter-calibration'). Here a good thematic match between the habitat classes observed in-situ and those mapped through EO and limiting the difference in spatial resolution (minimum mappable unit) between the in-situ and EO products appeared to be important. A thorough testing of this option across a variety of landscapes is recommended.

The most promising option was to use an independent but less accurate EO layer to post-stratify the in-situ samples. This option delivers a more precise sample-based estimates without requiring a good thematic match between the in-situ and EO layer or a very accurate EO land cover map. The next steps would be to test this option further across a variety of landscapes using a range of in-situ sample sizes.

Using the in-situ samples to train the classification of EO data, initially appeared to be an attractive proposition, however it became clear that a sampling strategy designed for EO image training, classification and validation is unlikely to suit the purpose of delivering unbiased and precise estimates of habitat extend and vice versa. An unsupervised classification of the EO imagery will quickly help establish whether the planned in-situ sampling strategy is representing the spectral range found in the imagery.

Using EO to increase the number of in-situ samples to increase precision, is a viable option only if the EO sample and the in-situ sample partly overlap so that omission error, commission error and bias can be estimated. It is also crucial that the overlapping part of both samples is a spatially balanced, random sample to avoid bias.

There is a critical need to accurately document costs associated to field surveying and, more urgently, the EO mapping effort. Without this information it is not possible to assess the cost-effectiveness of the options considered.

High spatial resolution EO imagery (aerial photography, hyperspectral airborne imagery and LiDAR) can be used very effectively to delineate parcel boundaries prior to the surveying of the in-situ sample. A thorough study involving a range of test cases which represent a variety of landscape and habitat types is required to establish whether automated approaches to delineate the parcels are more cost effective, consistent and precise than manual interpretation.

7. References

Arino, O., Trebossen, H., Achard, F., Leroy, M., Brockman, C., Defourny, P. (2005) The GLOBCOVER Initiative, Proceedings of the MERIS (A)ATSR Workshop 2005 (ESA SP-597). 26 - 30 September 2005 ESRIN, Frascati, Italy. Editor: H. Lacoste. Published on CDROM., pp.36.

Asner, G. P., Wessman, C. A., Schimel, D. S., and Archer, S. (1998), Variability in leaf and litter optical properties: implications for BRDF model inversions using AVHRR, MODIS, and MISR. Remote Sens. Environ, 63:243–257.

Asner, G.P., Martin, R.E. (2011) Canopy phylogenetic, chemical and spectral assembly in a lowland Amazon forest, New Phytologist, 189, 999-1012.

Barr, C. J.; Bunce, R. G. H.; Clarke, R. T.; Fuller, R. M.; Furse, M. T.; Gillespie, M. K.; Groom, G. B.; Hallam, C. J.; Hornung, M.; Howard, D. C.; Ness, M. J.. 1993 Countryside Survey 1990: main report. (Countryside 1990 vol.2). London, Department of the Environment, 174pp. (ITE Project No:T02051m5)

Bartholomé, E., Belward, A. S. (2005) GLC2000: a new approach to global land cover mapping from Earth observation dat,a International Journal of Remote Sensing, 26(9): 1959-1977.

Boyd, D.S. Danson, F.M.(2005) Satellite remote sensing of forest resources: three decades of research development, Progress in Physical Geography, 29(1): 1–26.

Bunce et al. 2008 Landscape Ecology, 23:11–25

Curran, P. J., Dungan, J. L., Macler, B. A., Plummer, S. E., and Peterson, D. L. (1992), Reflectance spectroscopy of fresh whole leaves for the estimation of chemical concentration. Remote Sens. Environ, 39:153–166.

Delbart N, Le Toan T, Kergoat L and Fedotova V (2006). Remote sensing of spring phenology in boreal regions: A free of snow-effect method using NOAA-AVHRR and SPOT-VGT data (1982-2004). Remote Sensing of Environment, 101, 52-62

Estreguil C., Vogt, P., Ostapowick (submitted) European level assessment of the status and trends of forest spatial patterns, Environmental Monitoring and Assessment Journal.

Engberg, A., 2005. Produktspecifikation av Svenska CORINE Marktäckedata (in Swedish). Lantmäteriet, Gävle, Document No SCMD-0001. Available online at: http://www.lantmateriet.se/upload/filer/kartor/kartor_och_geografisk_info/GSD-Produktbeskrivningar/SCMDspec.pdf

Eva, H.D., Belward, A.S., De Mirandaw,E.E., Di Bellaz, C.D., Gond, V.R., Hub Er, O., Onesk,S.J., Sgrenzaroli, M. and Steffenfritz (2004) A land cover map of South AmericaGlobal Change Biology (2004) 10, 1–14.

Friedl, M.A., D. K. McIver, J. C. F. Hodges, X. Y. Zhang, D. Muchoney, A. H. Strahler, C. E. Woodcock, S. Gopal, A. Schneider, A. Cooper, A. Baccini,F. Gao, C. Schaaf (2002) Global land cover mapping from MODIS: algorithms and early results, Remote Sensing of Environment, Vol. 83 (1-2): 287-302.

Fuller, R.M.,Wyatt, B.K., Barr, C.J., 1998. Countryside survey from ground and space: different perspectives, complementary results. J. Environ. Manag. 54, 101–126.

Fuller, R. M.; Cox, R.; Clarke, R. T.; Rothery, P.; Hill, R. A.; Smith, G. M.; Thomson, A. G.; Brown, N. J.; Howard, D. C.; Stott, A. P.. 2005 The UK land cover map 2000: Planning, construction and calibration of a remotely sensed, user-oriented map of broad habitats. *International Journal of Applied Earth Observation and Geoinformation*, 7. 202-216Gates, D. M., Keegan, H. J., Schleter, J. C., and Wiedner, V. R. (1965), Spectral properties of plants. Appl. Opt. 4:11–20.

Galego, J and Bamps, C., 2008. Using CORINE land cover and the point survey LUCAS for area estimation. International Journal of Applied Earth Observation and Geoinformation 10: 467–475.

Gerard, F., Plummer, S., Wadsworth, R., Ferreruela, A., Iliffe, L., Balzter, H. and Wyatt, B., 2003. Forest Fire Scar Detection in the Boreal forest with multi-temporal SPOT-VEGETATION data. IEEE transactions on Geoscience and Remote Sensing,41, 2575- 2585.

Gitelson, A. A. and M. N. Merzlyak. 1997. Remote estimation of chlorophyll content in higher plant leaves. International Journal of Remote Sensing, 18:2691–2697

Goel, N. S. (1988), Models of vegetation canopy reflectance and their use in estimation of biophysical parameters from reflectance data. Remote Sens. Rev. 4:1–212.

Hill R, Wilson A, George M (submitted) Mapping tree species in temperate deciduous woodland using time-series multi-spectral data, Journal of Applied Vegetation Science.

Hill, R. A.; Smith, G. M.. 2004 CS2000 Module 9. Data integration for localised results and support for indicators of countryside character and quality. Reports A4 - February 2004. NERC/Centre for Ecology and Hydrology, 34pp. (C02124) (Unpublished)

Hill R, Thomson A. (2005) Mapping woodland species composition and structure using airborne spectral and LiDAR data, International Journal of Remote Sensing, 26, 3763–377

Homer, C., Dewitz, J., Fry, J., Coan, M., Hossain, N., Larson, C., Herold, N., McKerrow, A., VanDriel, J.N. & Wickham, J., 2007. Completion of the 2001 National Land Cover Database for the conterminous United States. Photogrammetric Engineering and Remote Sensing 73: 337-341.

Jacquemoud, S., Baret, F., and Hanocq, J. F. (1992), Modeling spectral and bidirectional soil reflectance, Remote Sens. Environ. 41:123–132.

Jakubauskas M, Legates D, Kastens J (2002) Crop identification using harmonic analysis of time-series AVHRR NDVI data, Computers and Electronics in Agriculture, 37,127-139

Krauss, J., Bommarco, R., Guardiola, M., Heikkinen,R.K., Helm, A., Kuussaari,.M., Lindborg, R., Ockinger, E., Meelis, M., Pino, J., Poyry, J.., Raatikainen, K.M., Sang, A., Stefanescu, C., Teder, T., Zobel, M., and Steffan-Dewenter,S. 2010. Habitat fragmentation causes immediate and time delayed biodiversity loss at different trophic levels. Ecology Letters, (2010) 13: 597–605

Kumar Joshi, P.K. , Roy, P.S., Singh, S., Agrawal, S., and Yada, D. (2006) Vegetation cover mapping in India using multi-temporal IRS Wide Field Sensor (WiFS) dataRemote Sensing of Environment 103:190–202.

Li, H., Wu, J., 2004. Use and misuse of landscape indices. Landscape Ecology 19, 389–399.

Lillesand T, Kiefer R (1994) Remote Sensing and Image Interpretation, Third Edition: John Wiley and Sons Inc.

Loveland, T. R. and A. S. Belward, 1997, The IGBP-DIS global 1km land cover data set, DISCover: first results International Journal of Remote Sensing, 18, 3289-3295.

McRoberts, R.E., Wendt, D.G., Nelson, M.D. & Hansen, M.H., 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., Holden, G.R., Nelson, M.D., Liknes, G.C., and Gormanson, D.D, 2006, Using satellite imagery as ancillary data for increasing the precision of estimates for the Forest Inventory and Analysis program of the USDA Forest service. *Canadian Journal of Forest Research*, 36: 2968-2980.

Medcalf, K., Turton, N., Finch C. (2011) Making Earth observation work for UK biodiversity conservation. DEFRA/JNCC project report EnvSys/TEO_07-A, pp.83.

Metzger, M. J., Bunce, R. G. H., Jongman, R. H. G., Mücher, C. A. and Watkins, J. W. (2005), A climatic stratification of the environment of Europe, Global Ecology and Biogeography, 14(6): 549-563.

Moody A, Johnson D (2001) Land-surface phenologies from AVHRR using the discrete fourier transform, Remote Sensing of Environment, 75, 305-323

Moss, D. & Davies, C.E. 2002. Cross-references between the EUNIS Habitat Classification and the nomenclature of CORINE Land Cover European Topic Centre on Nature Protection and Biodiversity, Paris.

Myneni, R. B., Ross, J., and Asrar, G. (1989), A review on the theory of photon transport in leaf canopies. Agric. For. Meteorol.45:1–153.

Nilsson M., Folving, S., Kennedy, P., Puumalainen, J., Cincinati, G., Corona, P., Marchetti, M., Olsson, H., Ricotta, C., Ringvall, A., Ståhl, G., and Tompoo, E., 2003. Combining remote sensing and field data for deriving unbiased estimates of forest parameters over large regions. In: Corona, P., Köhl, M., and Marchetti, M. (eds.) Advances in Forest Inventory and for Sustainable Forest Management and Biodiversity Monitoring. Kluwer Academic Publishers, Forestry Sciences pp. 19-32

Nilsson, M., Holm, S., Wallerman, J., Reese, H. and Olsson, H., 2009. Estimating annual cuttings using multi-temporal satellite data and field data from the Swedish NFI. International Journal of Remote Sensing, 30:5109-5116.
Oldeland, J., Wesuls, D., Rocchini, D., Schmidt, M., Jürgens, N. , 2010. Does using species abundance data improve estimates of species diversity from remotely sensed spectral heterogeneity? Ecological Indicators 10: 390-396.
Palmer, M.W., Earls P.G., Hoagland B.W., White P.S., Wohlgemuth T. (2002) Quantitative tools for perfecting species lists, Envirometrics, 13: 121-137.
Paradella W, Da Silva M, Rosa N. Kushigbor C (1994). A geobotanical approach to the tropical rain forest environment of the Carajas mineral province (Amazon region, Brazil), based on digital TM-Landsat and DEM data. International Journal of Remote Sensing, 15, 1633-1648.
Peñuelas, J., J. Piñol, R. Ogaya, and I. Filella. 1997. Estimation of plant water concentration by the reflectance Water Index WI (R900/R970). International Journal of Remote Sensing 18:2869–2875
Reese, H.M., Lillesand, T.M., Nagel, D.E., Stewart, J.S., Goldmann, R.A., Simmons, T.E., Chipman, J.W. & Tessar, P.A., 2002. Statewide land cover derived from multiseasonal Landsat TM data - A retrospective of the WISCLAND project. *Remote Sensing of Environment* 82: 224-237.
Ross, J. K. (1981), The Radiation Regime and Architecture of Plant Stands, Kluwer Boston, Hingham, MA.
Schmidtein, S., & Sassin, J. (2004) Mapping of continuous floristic gradients in grasslands using hyperspectral imagery, Remote Sensing of Environment, 92: 126-138
Strand, H., Höft, R., Strittholt, J., Miles, L., Horning, N., Fosnight, E., eds. (2007). Sourcebook on Remote Sensing and Biodiversity Indicators. Secretariat of the Convention on Biological Diversity, Montreal,Technical Series no. 32: pp. 201.
Thomas, J. R., Namken, L. M., Oerther, G. F., and Brown, R. G. (1971), Estimating leaf water content by reflectance measurements. Agron. J. 63:845–847.
Thunnissen, H., de Wit, A. (2000) The National Land Cover Database of The Netherlands , ISPRS, Vol. XXXIII, Amsterdam, 2000
US Geological Survey, Gap Analysis Program (GAP). February 2010. National Land Cover, Version 1.
Ustin, S.L., Roberts D.A., Gamon, J.A., Asner, G.P. and Green, R.O. 2004, Using imaging spectroscopy to study ecosystem processes and properties, BioScience, 54(6):523-534.
Walter-Shea, E. A., and Norman, J. M. (1991), Leaf optical properties. In Photon–Vegetation Interactions (R. B. Myneni and J. Ross, Eds.), Springer-Verlag, Berlin: 229–252.
Wessman, C. A. (1990), Evaluation of canopy biochemistry. In Remote Sensing of Biosphere Functioning (R. J. Hobbs and H. A. Mooney, Eds.), Springer-Verlag, New York, pp.
Yang, X., Skidmore, A.K., Melick, D., Zhou, Z., Xu, J. (2007) Towards an efficacious method of using Landsat TM imagery to map forest in complex mountain terrain in Northwest Yunnan, China, Tropical Ecology 48(2): 227-239

8. Annexes