EnMAP

Technical Report

Science Plan

of the Environmental Mapping and Analysis Program (EnMAP)

Kaufmann, H.; Förster, S.; Wulf, H.; Segl, K.; Guanter, L.; Bochow, M.; Heiden, U.; Müller, A.; Heldens, W.; Schneiderhan, T.; Leitão, P.J.; van der Linden, S.; Hostert, P.; Hill, J.; Buddenbaum, H.; Mauser, W.; Hank, T.; Krasemann, H.; Röttgers, R.; Oppelt, N.; Heim, B.

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1. Introduction

1.1 The EnMAP mission

The Environmental Mapping and Analysis Program (EnMAP) is a German hyperspectral satellite mission that aims at monitoring and characterising the Earth's environment on a global scale. EnMAP serves to measure and model key dynamic processes of the Earth's ecosystems by extracting geochemical, biochemical and biophysical parameters, which provide information on the status and evolution of various terrestrial and aquatic ecosystems. Once operating, EnMAP will provide unique data needed to address major environmental problems related to human activity and climate change. The mission's main objective is to study and decipher coupled environmental processes and to assist and promote the sustainable management of the Earth's resources. Despite being a primarily scientific mission, EnMAP has a clear potential to evolve towards operational service.

The EnMAP mission consortium comprises the Helmholtz Centre Potsdam - German Research Centre for Geosciences (GFZ) as the principal scientific investigator, Kayser-Threde as the industrial prime contractor, OHB Systems AG providing the satellite service module, German Aerospace Agency (DLR) - Space Administration managing the project, and DLR Oberpfaffenhofen, which is responsible for the ground segment.

1.2 Scope of the document

The scope of this Science Plan is to describe the scientific background, applications, and activities related to the EnMAP mission. Primarily, the Science Plan addresses scientists and funding institutions, but it may also be of interest for environmental stakeholders and governmental bodies. It is conceived to be a living document that will be updated throughout the whole mission.

Current global challenges call for interdisciplinary approaches. Hence, the science plan is not structured in the traditional disciplinary way. Instead, it builds on overarching research themes to which EnMAP can contribute. This Science Plan comprises the following five chapters presenting the significance, background, framework, applications, and strategy of the EnMAP mission: Chapter 2 highlights the need for EnMAP data with respect to major environmental issues and various stakeholders. This chapter states the mission's main objectives and provides a list of research themes addressing global challenges to whose understanding and management EnMAP can contribute. Chapter 3 presents an overview of the EnMAP mission from a scientific point of view including a brief description of the mission parameters, data products and access, and calibration/validation issues. Chapter 4 provides an overview of hyperspectral remote sensing regarding its principles, development, and current state and synergies to other satellite missions. Chapter 5 describes current lines of research and EnMAP applications to address the research themes presented in Chapter 2. Finally, Chapter 6 outlines the scientific exploitation strategy, which includes the strategy for community building, dissemination of knowledge and increasing public awareness.

1.3 Terms and abbreviations

Throughout this document we use the term imaging spectroscopy synonymously for hyperspectral imaging. We refer to EnMAP as the hyperspectral imager containing two sensors, one for visual/near-infrared range and one for the shortwave-infrared range. Furthermore, we refer to the EnMAP satellite as the entity composed of the sensors and service module and to the EnMAP mission as all activities related to the EnMAP satellite. In the context of the EnMAP mission a wide spectrum of technical and management terms and abbreviations are used. The EnMAP mission team has built up a Glossary of Terms and Abbreviations that comprises contributions from many team members and is continuously updated and extended. The glossary is publicly available at http://www.enmap.org/cms.

2. Research context and significance

2.1 Major environmental challenges

Humanity faces fundamental challenges in the 21st century. Most prominently, we need to mitigate and adapt to climate change impacts, achieve a sustainable global land use, halt environmental degradation processes, and ensure resource sustainability. These closely linked aspects need to be understood, quantified, and managed as they put increasing pressure on society and the environment (*ESA*, 2006).

The interference of humankind with the Earth's atmosphere, biosphere, pedosphere, and hydrosphere has greatly increased during the last century. One of the most comprehensive impacts of these disturbances is the increase in air temperature, which is driven by increasing emissions of greenhouse gases. Over the last 50 years, Earth's mean near-surface air temperature increased by 0.13 °C per decade (*IPCC*, 2007). This trend in global warming drives a range of phenomena such as reduced snow and glacial cover, rising sea level, and increased occurrences of droughts and fires. These phenomena in turn show feedback mechanisms to the climate system via modifications in albedo, ocean circulation, and biogeochemical cycles.

Further global perturbations of the Earth System include the decline of water and air quality by widespread emission of pollutants and the decline of ecosystem services, which is interrelated to the loss of biodiversity, due to large-scale land cover changes. Nearly half of Earth's land surface has been transformed by direct human action with more than one quarter of the world's forests cleared (*Vitousek*, 1997) and one quarter of the land degraded (*FAO*, 2011). For several decades we reduced the diversity of life by polluting the environment, fragmenting habitats, spreading pathogens and invasive species, and changing global climate (e.g. *Dirzo and Raven*, 2003). These multiple, atypical high-intensity ecological stressors drive a continuous loss in biodiversity (*Barnosky et al.*, 2011) and compromise vital ecosystem services such as clean air, fresh water, and food (e.g. *Loreau et al.*, 2001).

Over the next 50 years, increased population and improved living standards are expected to prompt major increases in global food demand (*von Braun et al.*, 2005). Resulting increases in food production will be driven in large by intensified land use because further expansion of arable land area is limited and freshwater supplies are diminishing (*IGOS*, 2008). Likewise, the increasing demand of rising population numbers and growing economies for resources like energy, food, water, and land will remain a major driver of global change and environmental degradation. In turn, climate change and environmental stress will continue to put increasing pressure on many vulnerable communities. Extreme weather conditions like tropical cyclones, rainstorms, and heat waves resulted repeatedly in loss of life, property, and agricultural goods (e.g. *IPCC*, 2012). Further hazards like floods and landslides are associated with the continuous sea level rise, permafrost degradation, and widespread glacial retreat (*Kollmair and Banerjee*, 2011; *Vafeidis et al.*, 2011). In essence, we need to understand and quantify the consequences of human activities as a scientific basis for policy, decision-making, planning, and a sustainable land and resource management.

Our ability to address these increasingly urgent risks also depends on an improved detection and understanding of relevant processes. During the past decades hyperspectral remote sensing emerged as a valuable tool to assess and quantify a broad range of surface processes within the Earth System (e.g. *Goetz et al.*, 1985; *Schaepman et al.*, 2009). The availability of high quality hyperspectral imagery on a frequent basis will thus significantly contribute to the understanding of coupled processes and complex feedback mechanisms across different spheres. Against this background, EnMAP represents an ambitious mission to offer accurate, diagnostic information on the state and dynamics of terrestrial and aquatic ecosystems. Its future capability to repeatedly observe various locations of the Earth's surface in a high spatial and advanced spectral resolution opens up new possibilities to characterize ecosystem conditions (i.e. vegetation state, water quality, and soil properties) and to assess future trends. EnMAP is of key importance to monitor environmental degradation and change and it will contribute to improved concepts for sustainable management of land and other natural resources.

2.2 EnMAP mission objectives

The main scientific goal of the hyperspectral EnMAP mission is to study environmental changes, investigate ecosystem responses to human activities, and monitor the management of natural resources. By measuring diagnostic parameters that quantify the state and trend of environmental change, the stability of ecosystems, and the sustainability of resource use, the EnMAP mission aims to provide critical information for an improved understanding and management of the Earth System.

The primary mission objectives are:

- to provide high-quality calibrated hyperspectral data for advanced remote sensing analyses;
- to foster and develop novel methodologies that improve the accuracy of currently available remote sensing information and to provide advanced science-driven information products;
- to obtain diagnostic geochemical, biochemical and biophysical parameters that describe the status and dynamics of various ecosystems to improve our understanding of complex environmental processes;
- to provide information products that can serve as input for advanced ecosystem models;
- to significantly contribute to environmental research studies, particularly in the fields of ecosystem functions, natural resource management, natural hazards and Earth system modelling; and
- to develop new concepts and techniques for data extraction and assimilation to achieve synergies with other sensors.

EnMAP will significantly increase the availability of currently infrequent hyperspectral measurements covering large areas. To understand and fully exploit the information content provided by EnMAP, novel evaluation techniques need to be developed which fully utilize EnMAP's regional coverage on a global scale. EnMAP data will provide the unique opportunity to adapt and extrapolate existing hyperspectral acquisition and data analysis approaches derived from laboratory-, field-, and airborne measurements to spaceborne imagery. Their integration in regional ecosystem models will allow to complement, enhance, and extend current local case study findings to a regional scale. Consolidated and improved regional scale science on the state and evolution of ecosystems is the prerequisite for improvements in global ecosystem models. Such upscaling studies require a sensible generalisation of the derived quantitative ecosystem parameters and the synergistic analysis with other spaceborne imagery such as provided by the future Sentinel fleet.

Owing to the 30° across track off-nadir pointing capability, EnMAP is highly suited for repeated coverage of multiple key target sites with a maximum revisit cycle of 4 days. This ability allows EnMAP to repeatedly observe a globally distributed network of local to regional key target sites during its five years of mission operation. Based on this multiple-observation strategy EnMAP will provide highly resolved time-series to decipher the response of different ecosystems on natural and man-made pressures, such as climate change, urban sprawl, land use changes, natural hazards, and environmental pollution. This overall aim is linked to several secondary objectives that tackle pressing research topics as presented in the following section.

2.3 Overarching research themes

EnMAP's repeated observations with an advanced spectral coverage and resolution will provide new insights into multiple interrelated environmental subjects. The EnMAP Core Science Team identified several research topics, grouped in five major environmental themes, to which EnMAP data can provide a substantial contribution. Because hyperspectral image analysis is applicable to a wide range of research topics this selection focuses only on some of the most challenging environmental subjects.

Terrestrial Ecosystems

Keywords: Ecosystem services, Biodiversity, Species migration, Precision farming, REDD, Urban growth

- Quantifying the impact of human activities such as land use/cover change, land management practices, and environmental pollution on ecosystems, their services and biodiversity.
- Quantifying the rate and consequences of ecosystem changes (e.g. biodiversity loss, species migration).
- Monitoring measures to combat biodiversity loss and improve ecosystem stability (e.g. REDD+).
- Assessing the impact of soot and dust on snow and glacial melt and the consequences for the hydrological cycle.
- Analysing the state and development of urban compositions and growth.

Aquatic Ecosystems

Keywords: Water quality, Water constituents, Environmental pollution, Phytoplankton diversity

- Assessing the impact of environmental pollution on water quality.
- Analysing the spatiotemporal variability of phytoplankton and other water constituents, which provide insights in aquatic ecological changes.
- Discriminating water constituents (e.g. chlorophyll) to assess the water quality of freshwater reservoirs and aquaculturally used coastal and inland water bodies.
- Analysing type, status, and changes of shallow sea/lake bottom substrate (e.g. vegetation types, sediment dynamics).

Natural Resource Management

Keywords: Mineral deposits, Soil properties, Environmental rehabilitation

- Developing methods to explore and manage geo-resources, such as ore/mineral deposits and petroleum, in a sustainable way.

- Quantifying the extent of environmental pollution caused by mine wastes and monitoring the environmental rehabilitation progress.
- Monitoring measures to support sustainable resource management (e.g. forest ecosystems, arable land).

Hazards and Risks

Keywords: Disaster management, Extreme weather conditions, Landslides, Volcanoes, Floods, Land degradation, Oil spills, Marine debris, Industrial waste

- Quantifying the degree and extend of destruction in the event of a natural disaster to provide a coordinated short-term emergency response and a long-term risk management.
- Analysing the impact of extreme weather conditions (e.g. droughts, heat waves, hurricanes) on ecosystems and agriculture.
- Quantifying the degree and extent of environmental pollution caused by oil spills, marine litter, mine wastes, or industrial chemicals and the environmental rehabilitation progress.
- Quantifying land degradation processes (e.g. desertification, salinization, soil acidification, soil erosion) and their impact on ecosystem services.
- Assessing the susceptibility of areas/communities towards natural hazards (e.g. fires, floods, landslides) and the rate and nature of change in their vulnerability.

Atmospheric Research

Keywords: Columnar water vapour, Mineral dust, Pollen

- Improve algorithms to retrieve columnar water vapour, mineral dust, particulate matter clouds and pollen.

2.4 European and International stakeholders

The products and information generated from EnMAP data will be of substantial interest for the scientific community, several European and International organizations, and the general public. References to the following organizations, initiatives and agreements can be found in the Annex (Table A.1).

First and foremost, researchers need EnMAP data to improve their understanding of Earth surface processes and reduce uncertainties in associated ecosystem models. Scientific requirements for terrestrial observations have long been articulated, especially at the international level, by the International Geosphere-Biosphere Program (IGBP), the Land Ocean Interaction in the Coastal Zone Program (LOICZ), the International Human Dimensions Program (IHDP), DIVERSITAS, the World Climate Research Program (WCRP), Global Land Project (GLP), Global Biodiversity Information Facility (GBIF), Millennium Ecosystem Assessment (MA), and the Global Environment Outlook (GEO) (*GLP*, 2005). The major new "Future Earth" alliance on Earth system research for global sustainability integrates and consolidates the above mentioned international expertise in environmental and social science under one umbrella and forms the programmatic and societal justification for the EnMAP-based science.

Key international stakeholders, who rely in their future work on the scientific results of the EnMAP mission, include organizations that make up the United Nations System (e.g. UNEP, FAO, UNESCO and WMO). Furthermore, selected UN System organizations, alongside the Intergovernmental Oceanographic Commission and International Council for Science, sponsor the Global Climate Observing Systems (GCOS), Global Ocean Observing System (GOOS) and Global Terrestrial Observing System (GTOS). These three bodies are also important stakeholders as they provide advice on needs, gaps, and future developments of observations as required by the UN System, by multilateral environmental agreements (REDD+, UNFCCC, UNCCD, CBD, etc.), and by associated key entities, such as the Intergovernmental Panel on Climate Change (IPCC), the Intergovernmental Platform on Biodiversity & Ecosystem Services (IPBES) and the International Union for Conservation of Nature (IUCN) (*IGOS*, 2008).

At the level of the European Union several Commission directories (e.g., DG VI - Agriculture, DG VIII - Development, DG XI - Environment, DG XII - Transport, and DG XVI - Regional policy) are anticipated to require continuous remotely sensed land observations because these governmental departments need to set, monitor, and enforce their policy agenda. For example, specified biological, hydromorphological and physico-chemical parameters of water bodies have to be monitored on a regular basis according to the EU Water Framework Directive. In addition, national/local authorities will need increasingly detailed information for implementing local measures to combat desertification and to plan alternative land uses. Furthermore, this information will be useful in meeting the objectives of the action plans concerning the protection of the Mediterranean Sea against telluric pollution (Barcelona Convention, Mediterranean Action Plan). Against this background, data products (e.g., soil status, vegetation cover, change detection maps, degradation index maps) will be beneficial for decision makers. In particular, the European Earth monitoring programme GMES (Global Monitoring for Environment and Security) requires environmental information to support critical decisions of policymakers and public authorities on environmental legislation and policies with a particular focus on climate change and natural or man-made catastrophes.

Furthermore, the general public has an increasing interest in many aspects of global environmental change, which is also reflected by political developments. The Aarhus Convention codifies the European citizen's participation in environmental issues and provides a legal framework for access to information on the environment held by public authorities (*IGOS*, 2008).

3. General mission framework

3.1 Technical parameters

The EnMAP satellite carries a push-broom type hyperspectral imager, that records reflected radiation from the Earth surface in the wavelength region from 420 nm to 2450 nm via 242 contiguous bands. The visible/near infrared (VNIR) range is covered by 88 bands with a mean band width of 6.5 nm and the short wave infrared (SWIR) range is covered by 154 bands with a band width of 10 nm. Accurate radiometric and spectral responses are ensured by a sufficient signal-to-noise ratio of $\geq$400:1 in the VNIR and $\geq$170:1 in the SWIR (based on an albedo of 30% and a solar zenith angle of 30°), a radiometric calibration accuracy of better than 5%, and a spectral calibration uncertainty of 0.5 nm in the VNIR and SWIR.

The sensor is characterized by a ground sampling distance of 30 m (nadir at sea level) and provides a swath width of 30 km. EnMAP can record strip lengths of up to 1000 km with a capacity of 5000 km per day. The nominal target revisit time of 23 days can be reduced to 4 days by use of the across track off-nadir pointing capability of ±30°. EnMAP will be launched in a sun-synchronous orbit (653 km height at 48°N; 97.96° inclination) with a local equatorial crossing time of 11:00 hr. The satellite launch is scheduled for 2016 with an Indian "Polar Satellite Launch Vehicle" and has a designed lifetime of five years. A summary of all mission/instrument details is given in Table 1.

3.2 Data processing, calibration, and validation

Hyperspectral data are usually supplied as spectral radiance data (e.g. Watts per square centimetre per steradian per micrometre). The identification of pigments and materials such as minerals is based on the spectral reflectance characteristics of the target surface. Consequently, the internal calibration of the sensor and the methodological approach in the conversion of at-sensor radiance into surface reflectance are of utmost importance for the accuracy and subsequent processing and evaluation of data. The conversion processes from radiance to spectral reflectance involve three main steps. The first step accomplishes the normalisation of the radiance data by the actual spectral solar insolation intensity for each spectral band of the given sensor (*Thuillier et al.*, 1998; *Green and Gao*, 1993; *Staenz et al.*, 1995). This transforms the radiance data acquired by a sensor into at-sensor bi-directional reflectance data. Secondly, the at-sensor-reflectance-data are converted into surface-reflectances through the application of an atmospheric correction scheme, which compensates for atmospheric scattering (Rayleigh and Mie), molecular absorption (H_2O, O_2, O_3, CO_2, NO_2 or CH_4), and aerosols (*Conel et al.*, 1988; *Berk et al.*, 1998; *Richter*, 1996). The third step contains the correction of these surface reflectance spectra for relief (elevation, slope and aspect) and macroscopic surface roughness (*Richter*, 1998). The resulting reflectance spectra can then be compared to existing spectral libraries compiled mainly from laboratory and field measurements. The comparison is also dependent on BRDF (Bidirectional Reflectance Distribution Function) characteristics of the target (different illumination and observation geometry) and mixed-pixel problems.

Table 1: EnMAP satellite parameters

EnMAP	Parameter	Performance	
Satellite characteristics			
	Imaging principle	push-broom, two prism imaging spectrometers	
	Orbit	sun-synchronous	
	Altitude	643 km	
	Inclination	97.96°	
	Weight (payload + bus)	1000 kg	
	Size	3.1 m × 1.9 m × 1.7 m	
Spectral characteristics		*VNIR*	*SWIR*
	Spectral range	420 - 1000 nm	900 - 2450 nm
	Number of bands	88	154
	Spectral sampling interval	6.5/10 nm	10 nm
	Spectral bandwidth (FWHM)	8.1 ± 1.0 nm	12.5 ± 1.5 nm
	Signal-to-noise ratio (SNR)	> 400:1 (at 495 nm)	> 170:1 (at 2200 nm)
	Spectral calibration accuracy	0.5 nm	
	Spectral stability	0.5 nm	
	Spectral smile/keystone effect	< 20 % of detector element	
	Radiometric calibration accuracy	< 5 %	
	Radiometric stability	± 2.5 % between two consecutive calibrations	
	Polarisation sensitivity	< 5 %	
Spatial characteristics			
	Ground sampling distance (GSD)	30 m (at nadir; sea level)	
	Swath width	30 km (Field of View = 2.63° across track)	
	Swath length	1000 km/orbit - 5000 km/day	
	Pointing angle	±30° (across track)	
	Geometric co-registration	≤ 0.2 x GSD	
	Pointing accuracy	500 m nadir	
	Pointing knowledge	100 m nadir	
	Pointing stability	< 5 % of a pixel (short term jitter)	
Temporal characteristics			
	Target revisit time	23 days (VZA ≤ 5°) / 4 days (VZA ≤ 30°)	
	Equator crossing time	11:00 h ± 18 min (local time descending node)	
	Average Ground Speed	6.9 km/s	
	Along-track exposure	4.3 ms	

Based on the aforementioned processing steps, the mission requires a well-characterized primary sensor, on-board calibration facilities with ongoing vicarious calibration measurements to provide a continuous sensor performance validation. Only well calibrated instruments with validated performance data are able to produce reliable data throughout the entire mission lifetime. The derived information products also require independent validation, by means of field and image measurements.

The pre-flight sensor characterization is performed in the laboratory for both, the individual subsystems and the complete end-to-end sensor system. It includes spectral, radiometric, and geometric calibrations. The spectral measurements include the band centres, bandwidths, and spectral response profiles for each band of each pixel in the array. These are required for a meaningful use of the data and for the performance of the radiometric calibration of the sensor. The radiometric measurements include the detector array responsivity, linearity, uniformity, noise characterization, straylight, and optics transmittance with the objective to provide reliable radiance data, which meet the signal-to-noise requirements of the mission. The geometric measurements include the total field of view, the view angle for each pixel and each band, and the modulation transfer function. After launch, in-flight calibration is carried out using onboard calibration devices such as the *Solar Full Aperture Diffuser* for the absolute radiometric calibration using the sun as the known reference, a *Main Sphere* for the relative radiometric calibration, a *Small Sphere* for spectral characterization, *Focal Plane Assembly LEDs* for non-linearity calibration and a *Shutter* for dark current calibration. These measurements will be complemented by vicarious calibration experiments on demand. As the imaging spectrometer and the on-board calibration instrumentation age, there is a growing need for periodic in-flight calibration vicarious and on-board calibrations.

Validation of the EnMAP L1, L2geo, L2atm and L2 products (see section 3.3) will be performed during the commissioning phase and the operational mission period. The validation procedure includes ground- and scene-based techniques for the product evaluation to derive characteristic error estimates for the final EnMAP products and detailed information to track potential error sources back to instrument and processing chain levels. These validation results will be incorporated in calibration activities and will be provided as additional information on the instrument spectral and radiometric performance. The purpose of these calibration and validation measurements is to provide data products with a high radiometric and geometric accuracy throughout the operational mission time.

3.3 Data products and access

During the operation phase, the following four EnMAP data products will be delivered to the user community: Product Level 1, Product Level 2geo, Product Level 2atm, and Product Level 2. Please note that the raw data and its processed Level 0 (cf. Figure 1) product are not available to the user community.

The Level 1 product represents the top-of-atmosphere radiance. This product is radiometrically calibrated, spectrally characterized, geometrically characterized, quality controlled, and annotated with preliminary pixel classification (usability mask). The auxiliary information (e.g. position and pointing values, interior orientation parameters, gain and offset) necessary for further processing is attached, but not applied. The Level 1 processor corrects the hyperspectral image for known effects, e.g. radiometric non-uniformities, and converts the system corrected data to physical at-sensor radiance values based on the currently valid radiometric calibration values and dark current measurements.

The Level 2geo product represents geocoded top-of-atmosphere values. This product is derived from the Level 1 product, which is subsequently geometrically corrected (orthorectified) and re-sampled to a specified grid. Auxiliary data for further processing are attached, but not applied. The Level 2geo processor creates ortho-images by direct geo-referencing, utilizing an adequate digital elevation model. The extraction of ground-control-points from existing reference images using image matching techniques serve to improve the line-of-sight vector and therefore to increase the geometric accuracy of the ortho-images. The Level 2geo processor ortho-rectifies image tiles from the VNIR and SWIR instrument independently. After ortho-rectification the two image tiles are co-registered (better than 0.2 pixel size) and form a geometrically consistent product over the whole wavelength range.

The Level 2atm product represents scaled ground reflectance values. This product is derived from the Level 1 product. The data are then converted to ground surface reflectance values after an atmospheric correction that assumes a flat terrain. Auxiliary data for further processing are attached, but not applied. The Level 2atm processor will convert the physical at-sensor radiance values to surface reflectance values separately for land and water applications. This includes the estimation of the aerosol optical thickness and the columnar water vapour.

The Level 2 product represents the ground surface reflectance. This product is derived from the Level 2geo product, atmospherically corrected, and converted to ground surface reflectance values. Most applications are envisioned to use the Level 2 product for further analysis.

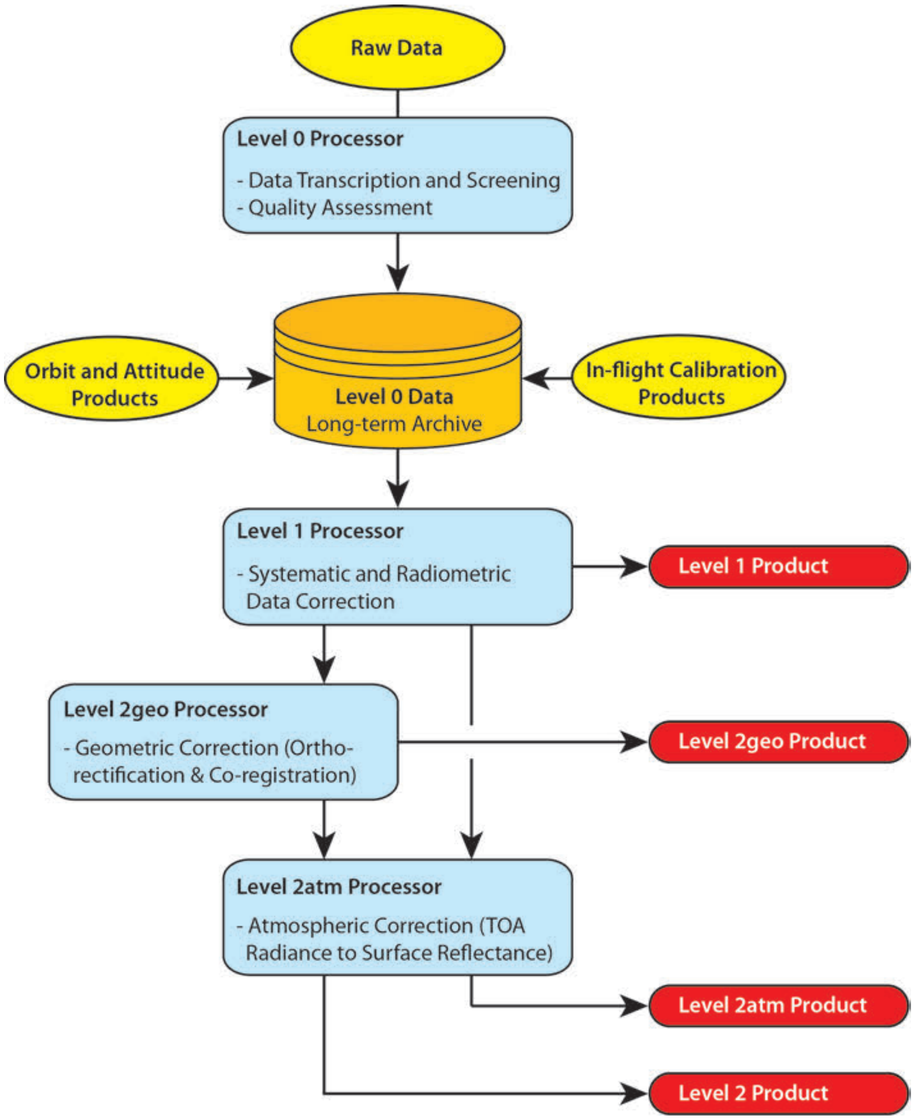

Figure 1: The EnMAP data processing chain from the raw data to the atmospherically and geometrically corrected level 2 product.

Access to EnMAP data should occur in a transparent and objective manner according to the UN resolution 41/65, 3 (1986) on *Principles on Remote Sensing of the Earth from Space*.

EnMAP data distribution differentiates between four user categories: (1) internal users, (2) scientific users, (3) private users, and (4) so-called "charter users". Internal users support the operation of EnMAP by calibrating and validating data, especially during the commissioning phase. Scientific users carry out research for non-commercial purposes, which also include the use for educational or developmental purposes. Private users employ data for operational or commercial tasks, which also include applications for the public domain. Charter users require data in the event of disasters or emergencies according to the *Charter On Cooperation To Achieve The Coordinated Use Of Space Facilities In The Event Of Natural Or Technological Disasters Rev.3 (25/4/2000)*.

Within the scope of *Announcements of Opportunities* the user community is called for project proposals concerning the pre-operational and scientific use of EnMAP. These proposals are envisioned to address the calibration and validation of EnMAP products and to develop algorithms and strategies for their analysis. In addition to these proposals all users can request archived data listed in a continuously updated data catalogue. After the end of the commissioning phase all data will be stored, maintained, and distributed by German Aerospace Agency (DLR) for at least 20 years.

The EnMAP portal (www.enmap.org) is the central entry point for all national and international users interested in learning about the EnMAP mission, its objectives, status, data products and processing chains. Additionally, this platform informs about the conditions and requirements for the EnMAP data access and the ongoing scientific programs and activities.

4. Hyperspectral remote sensing

4.1 Principles of imaging spectroscopy

Surface materials, such as vegetation, soil, and rock, can be discriminated and characterised based on their so-called *spectral signatures*, i.e. diagnostic absorption and reflection characteristics over the electromagnetic spectrum. Because every material is formed by chemical bonds, their harmonics and overtones of vibrational electronic transitions result in characteristic spectral absorption features that can be detected in narrow wavelength intervals. Some of the most significant absorption features occur between wavelengths of 400 nm to 2500 nm, where reflected solar radiation dominates the natural electromagnetic spectrum (Figure 2). These absorption characteristics can vary in their spectral depth, width, and location and therefore serve as diagnostic indicators, which enable us to characterize vegetation conditions (e.g. *Knipling*, 1970), to detect water constituents (*Lee et al.*, 1999), or to identify mineral assemblages (e.g. *Hunt and Salisbury*, 1970).

Imaging spectroscopy, also known as hyperspectral imaging, is defined as a passive remote sensing technology that acquires simultaneous images in many spectrally contiguous, registered bands such that for each pixel a reflectance spectrum can be derived (*Goetz et al.*, 1985; *Schaepman*, 2007). Application areas of hyperspectral sensing include ecosystem processes, surface mineralogy, water quality, soil type and erosion, vegetation type and condition, canopy chemistry, snow and ice properties, and extra-terrestrial research but it is also widely used in medicine, manufacturing industries, disaster management and national security.

In ecosystems studies the spectroscopic focus is on detection and identification of plant succession, phenology, plant health, and invasive species to provide information about ecosystem conditions, and particularly about the locations and types of environmental stresses (*Asner et al.*, 2008; *Schmidtlein and Sassin*, 2004; *Ustin et al.*, 2004). Because of the importance of photosynthetic function, most research has focused on the spectral properties of leaves and canopies that provide estimates of chlorophyll, water, dry matter, and nitrogen (*Turner et al.*, 2004). In general, the spectral characteristics of vegetation exhibit strong pigment absorptions in the visible portion of the spectrum (Figure 3). The near infrared (NIR: 700-1400 nm) is marked by a steep increase of reflectance that can be related to biomass, state and type of cellular arrangement, density, geometry and water content of a vegetation canopy. A shift of the "red edge" at 680 nm to 780 nm to shorter wavelengths is related to chlorophyll decrease, which can in turn be an indication of heavy metal, water or nutrient stress. The biochemical content of leaves and canopies, including nitrogen-containing compounds and lignin, absorbs radiation at fundamental stretching frequencies, generally in the NIR and SWIR regions. Senescent leaves follow a typical trajectory, with decreases in chlorophyll followed by losses of other pigments and water. Aging and stress increase reflectance over the visible and shortwave-infrared spectrum and decrease it in the near infrared (*Ustin et al.*, 2004). Consequently, imaging spectroscopy is highly suitable to quantify vegetation state and to distinguish between various vegetation species.

For geologic applications imaging spectroscopy is used to map Earth's surface composition (in terms of mineralogy or lithology) and for the quantification of rock and soil chemistry and physics based on

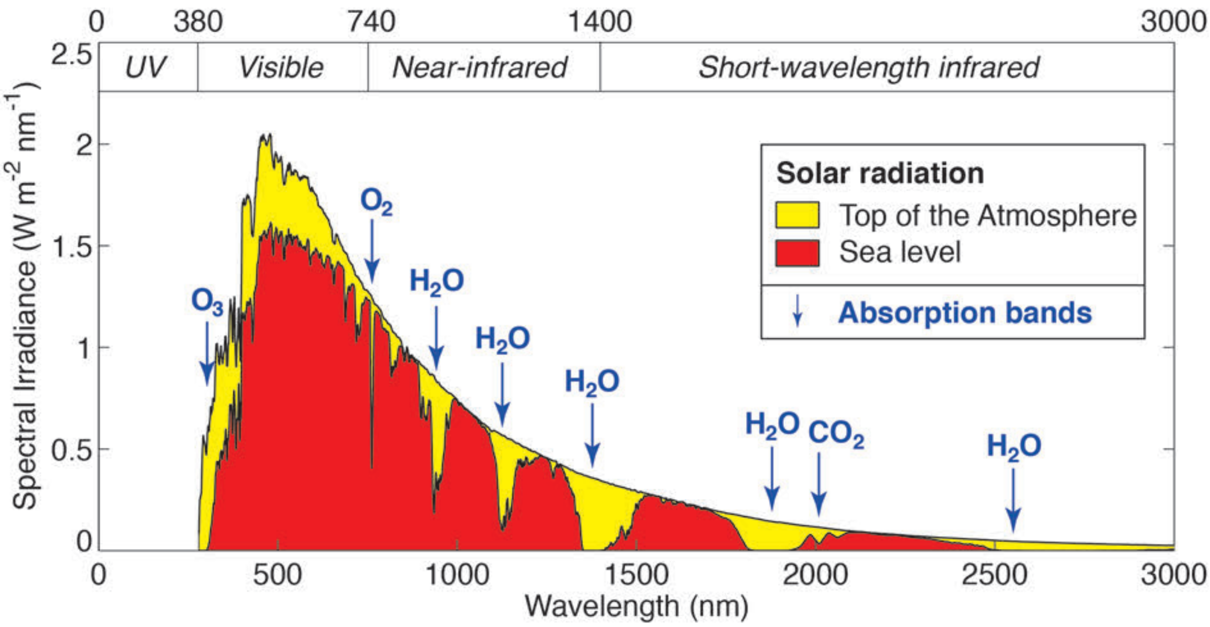

Figure 2: Solar radiation spectrum of extra-terrestrial radiation (Top of the Atmosphere) and global radiation (Sea level, composed of incoming, diffuse, and reflected radiation) with major atmospheric absorption bands. Irradiance data are derived from the American Society for Testing and Materials (ASTM) Terrestrial Reference Spectra (http://rredc.nrel.gov/solar/spectra/am1.5/).

spectral absorption features. Reflectance spectra of minerals are dominated in the VNIR wavelength range (400-1200 nm) by the presence or absence of transition metal ions (e.g., Fe, Cr, Co, Ni) resulting in absorption features due to electronic processes. The presence or absence of water and hydroxyl, carbonate and sulphate determine absorption features in the SWIR region (1400-2500 nm) due to vibrational processes. These phyllosilicates, sorosilicates, hydroxides, sulphates, amphiboles and carbonates are widespread components of the Earth surface. The absorption band depth is related to grain or particle size, as the amount of light scattered and absorbed by a grain is dependent on grain size (*van der Meer et al.*, 2012). In general, absorption band depth is correlated with the (relative) amount of material present. Based on relative absorption depth, for example, it has been shown that kaolinite and organic carbon content can be derived with an accuracy of about 2% by weight (*Krueger et al.*, 1998).

Soils are highly variable, dynamic components of the environment and are essential for ecosystem functions. Soils comprise a major repository for biospheric carbon, and organic matter in the topsoil. The degree to which these components are present or absent in the topsoil provide a good indication of soil quality, soil erosion, and physical processes such as hydraulic conductivity and soil aggregation. It has long been recognized that some soil properties have spectral features that can be detected using spectroscopy (*Ben-Dor et al.*, 1999). *Baumgardner et al.* (1986) identified five basic spectral shapes related to organic matter content, iron oxide content, and soil texture. In general, soils, like plants, have only a few recognizable narrow absorption features. Soils typically have broad, shallow absorption features related to iron oxides and organic matter at wavelengths between 400 and 2500 nm (Figure 3). Reflectance decreases as organic matter increases. Ferric or ferrous iron causes absorptions in the visible and near-infrared spectra, particularly around 860 nm. In contrast to organic matter and iron oxides, various clay minerals (e.g., montmorillonite, kaolinite, illite, smectite) and carbonates have distinctive narrowband absorptances in the shortwave-infrared region between 2000 and 2500 nm. However, hyperspectral quantification of soil properties is only suitable in landscapes with low vegetation cover (*Ustin et al.*, 2004).

Imaging spectroscopy has been widely used to monitor oceans and inland waters, which are char-

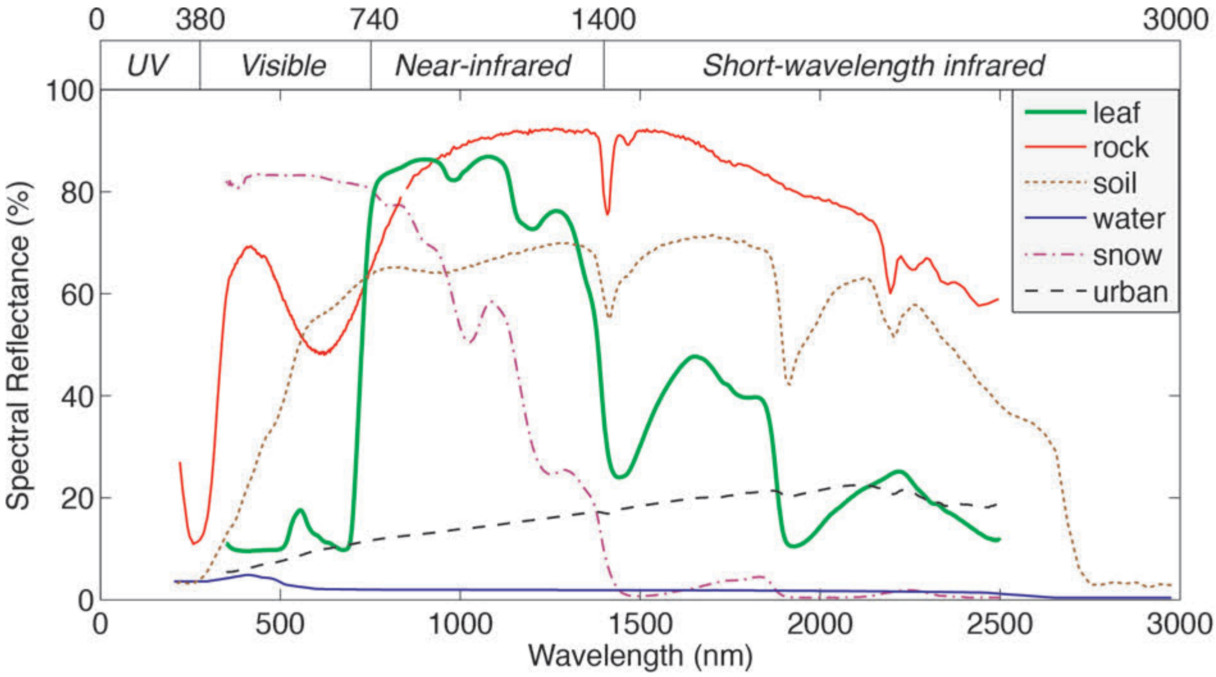

Figure 3: Reflectance spectra of selected Earth's surface components. Reflectance data are derived from the USGS Digital Spectral Library (http://speclab.cr.usgs.gov/spectral.lib06/). The laboratory measurements represent samples of an oak leaf from Colorado (leaf), Aventurine quartz from India (rock), Montmorillonite and Illite from Virginia (soil), seawater from the Pacific Ocean (water), fresh snow from Colorado (snow), and black road asphalt from Colorado (urban).

acterized by an overall high adsorption compared to land surfaces (Figure 3). This optical characteristic makes water suitable to isolate and measure its optical constituents, such as pigments (e.g. chlorophyll), a wide range of phytoplanktonic species, dissolved organics, and suspended non-algal particles (e.g minerogenic sediments). Coastal and inland waters are optically more complex as compared to open oceanic waters, which can be characterized mainly by one optical parameter and are generally referred to as case-1 waters (*Morel and Prieur*, 1977). In contrast, inland and coastal waters are influenced by multiple parameters, which have partly similar optical properties.

Alpine snow cover and its subsequent melt can dominate local to regional climate and hydrology in the world's mountainous regions. To model the snowmelt distribution and its impact hyperspectral remote sensing allows for the retrieval of snow properties like snow-covered area, albedo, grain size, liquid water very near the surface, and impurities (*Dozier and Painter*, 2004). Among natural materials at the Earth's surface, snow has a huge range of spectral reflectance values depending on its physical characteristics, primarily the grain size but also dust or soot content, organic substances such as algae, and liquid water (*Dozier et al.*, 2009). Clean, deep snow is highly reflective in the visible spectrum, whereas reflectance in the near-infrared and shortwave-infrared wavelengths shows a general decrease but vary considerable depending primarily on the grain size (Figure 3).

Urban areas are characterized by a wide range of spectrally distinct surface materials, whose spectral signature is determined by its chemical composition (*Heiden et al.*, 2012). For example, roofing tiles and polyethylene exhibit pronounced absorption features and high spectral variation, whereas other urban surfaces such as concrete and asphalt are characterized by low reflectance and low spectral variation.

EnMAP has the capability to detect individual absorption features in the spectra of many materials, solids, liquids, or gases. Actual detection depends on the instrument´s spectral coverage, spectral resolution, spectral sampling, signal-to-noise ratio, the abundance of the material, and the strength of the material's absorption features in the wavelength region measured. The spectral molecular absorption and scattering properties of materials, as mentioned in the previous paragraphs, form the basis for the identification and determination of the abundances of surface and atmospheric constituents. Accordingly, research and development efforts within the EnMAP mission employ these fundamental spectral characteristics as a basis for the extraction of information from spaceborne hyperspectral data.

Despite the numerous advantages over remotely sensed multispectral or panchromatic data, obtaining, (pre-)processing and analysing hyperspectral data is challenging in a variety of ways. (1) The physical data size of multidimensional imaging spectroscopy data increases linearly with the number of spectral bands. As a result, the data transfer from satellites to ground stations is limited by downlink capacities and processing of hyperspectral data is often time consuming. (2) Atmospheric absorption affects particularly hyperspectral data, which covers the full spectral range between approximately 400 and 2500 nm in narrow bandwidths. Therefore, selective absorption of atmospheric gases in narrow spectral regions or pronounced absorption by atmospheric water vapour in wider spectral regions requires sophisticated pre-processing. (3) An overall lower signal-to-noise ratio as compared to multispectral data is another issue related to narrow spectral bandwidths and atmospheric attenuations that calls for technological advances and requires advanced processing methods. (4) Another drawback of hyperspectral data is the significant band-to-band correlation, which results in dimensionality issues and consequently reduces the total amount of available bands. (5) Furthermore, analysis of imaging spectroscopy data needs to account for BRDF effects, which vary as a function of illumination and viewing geometry and depend on the wavelength as well as structural and optical properties of the surface.

To manage these and other challenges the scientific report "Hyperspectral Algorithms: Report in the frame of EnMAP preparation activities" by *Kaufmann et al.* (2010) composes the state of the art processing algorithms and methodologies to analyse imaging spectroscopy data in diverse research disciplines. Complementary, the EnMAP-Box represents a platform independent software interface, which facilitates a convenient and straightforward processing and analysing of EnMAP data. For further information refer to the EnMAP website (www.enmap.org).

4.2 Imaging spectroscopy missions

Nearly three decades of effort have been devoted to the development of imagers capable of acquiring contiguous spectra in different wavelength regions, thereby permitting precise and quantitative analysis of terrestrial and aquatic ecosystems. These imaging spectrometers have primarily been flown in aircrafts for experimental and commercial purposes (e.g., AIS, (*Vane et al.*, 1983) FLI and casi (*Gower et al.*, 1992), AVIRIS (*Vane et al.*, 1993), GER/DAIS (*Collins and Chang*, 1990), SFSI (*Neville and Powell*, 1992), Hydice (*Rickard et al.*, 1993), MIVIS (*Bianchi et al.*, 1994), HyMap (*Cocks et al.*, 1998), APEX (*Schaepman et al.*, 2004), AVIS *Oppelt and Mauser* (2007), AISA (www.spectralcameras.com/aisa), HySpex (www.hyspex.no), and Hyperspec (www.headwallphotonics.com)) (Figure 4). However, data acquisition from an aircraft platform is often restricted by various issues: Varying aircraft attitude changes make geo-referencing of the imagery difficult; the wider sensor field of view required by the low aircraft altitude generates bidirectional reflectance related problems; repeated acquisitions are costly; finally, synoptic viewing of extended areas is not possible. For a more complete overview of airborne imaging spectroscopy sensors and their history refer to *Schaepman* (2009).

In general, operational optical satellite sensors have been panchromatic or multispectral instruments operating in selected discrete bands in the VNIR region including in some cases bands in the SWIR and TIR region (e.g. Landsat, ASTER) of the spectrum. The panchromatic sensors provide only spatial information while the multispectral instruments, such as the traditional broadband systems Landsat TM, SPOT HRV/HRG, or IRS LISS, augment the spatial data with mainly qualitative information about the surface materials. Exceptions are the four launched hyperspectral sensors Hyperion by NASA (National Aeronautics and Space Administration) in 2000 (*Pearlman et al.*, 2003), CHRIS by ESA (European Space

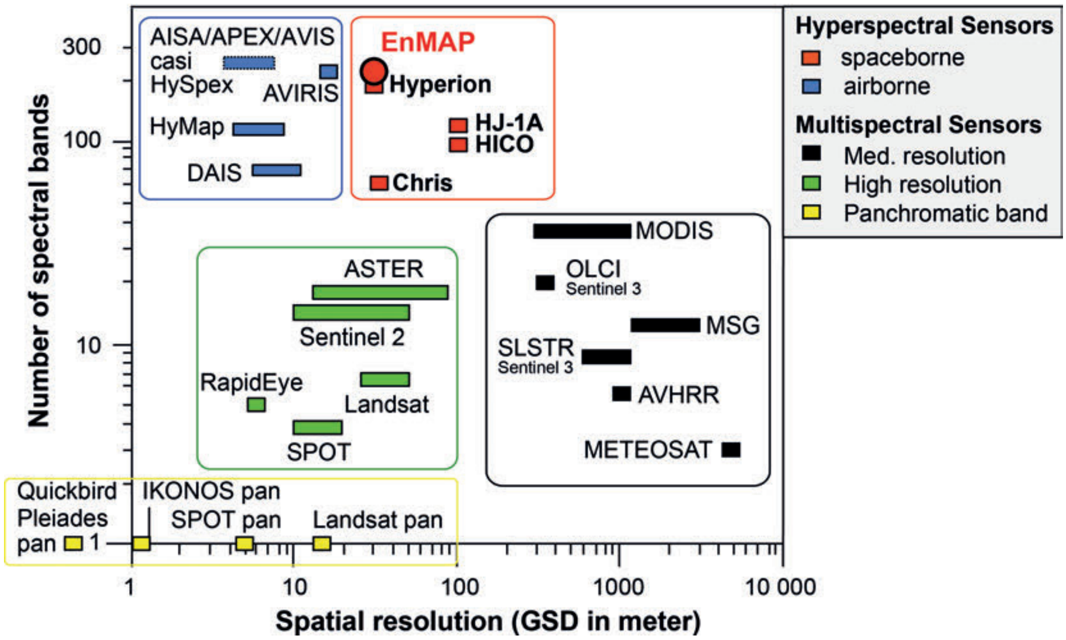

Figure 4: Overview of the spectral and spatial resolution of selected airborne and spaceborne hyperspectral and multispectral sensors.

Agency) in 2001 (*Barnsley et al.*, 2004), HJ-1A by CASC (China Aerospace Science and Technology Corporation) in 2008 and HICO by NASA in 2009 (*Corson et al.*, 2008) (Figure 4). Considering that Hyperion and CHRIS are still operating technology demonstrators, they provide exceptional results. Nonetheless, CHRIS, HICO and HJ-1A are limited to the VNIR region, while Hyperion is characterized by a low signal-to-noise ratio. Both of these factors limit the sensors in their feature detection capabilities. Therefore, current spaceborne sensors provide only limited information on biochemical and geochemical parameters, which are required for detailed environmental studies.

Against this background, the EnMAP mission represents a milestone towards an innovative comprehensive hyperspectral observation from space. Further imaging spectroscopy missions are prepared by ASI (Italian Space Agency) in the form of PRISMA (PRecursore IperSpettrale della Missione Operative), by JAXA (Japanese Aerospace Exploration Agency) in the form of HISUI (Hyperspectral Imager Suite), by NASA in the form of HyspIRI (Hyperspectral Infrared Imager), and by CNES (Centre National d'Études Spatiales) in the form of HYPXIM.

4.3 Synergies with other sensors

While EnMAP is conceived as a stand-alone mission with scientific objectives driven by the EnMAP scientific community and its advanced technical concepts, valuable synergies exist between optical and radar imagery as well as other geo data.

A large potential for synergies exists between EnMAP and ESA's future Sentinel missions (*Berger et al.*, 2012). The Sentinels aim at providing global coverage of high quality remote sensing data in the optical (0.4-2.5 µm) and microwave (40-80 mm) domain in both high and medium spatial resolution. These missions will serve the Global Monitoring for Environment and Security (GMES) programme by providing continuous and global Earth observation from space on an operational basis. The Sentinel fleet will form the global framework, into which the scientific results from EnMAP's globally distributed key target sites can be embedded to improve a new generation of global ecosystem models.

Sentinel-2 will provide Landsat/SPOT-like imagery in a high spatial (10-60 m) resolution and a moderate temporal (<5 days) and spectral (13 bands) resolution (*Drusch et al.*, 2012). Its global coverage in a comparable spatial resolution to that of EnMAP (30 m) holds the synergistic potential to expand EnMAP's advanced regional information to a global scale. Complementary, Sentinel-3 and similar medium-spatial-resolution optical missions, which will operate concurrently with EnMAP, provide global coverage data in an almost daily temporal resolution (*Donlon et al.*, 2012). Synergies between EnMAP and these sensors include more frequent ecosystem observations in order to resolve surface processes with high temporal variations.

In addition to optical sensors, Synthetic Aperture Radar (SAR) missions also provide complementary information to EnMAP data. For example, Sentinel-1 will operationally provide C-band SAR-data of the Earth's surface with spatial resolutions of up to 10-20 m (*Torres et al.*, 2012). This ability allows for analysing the state and variation of physical parameters, such as surface roughness and soil moisture, which complements EnMAP's strength to derive bio-geochemical properties of the Earth surface. Furthermore, digital terrain model (DTM) data as retrieved from TerraSAR-X or Tandem-X using InSAR techniques may serve for data correction purposes, such as the removal of geometric distortion effects in mountainous terrain (*Krieger et al.*, 2007).

The high spectral resolution of EnMAP can be combined with the current and future panchromatic and multispectral satellite systems like IKONOS, QuickBird, WorldView, RapidEye, Pleiades etc., which are characterized by a high to very high spatial resolution. Such sensors offer additional options to improve object recognition, product validation, and temporal coverage. For example, the high temporal and spatial resolution data provided by RapidEye (one day revisit, 6.5m GSD) can be combined with EnMAP to augment temporal coverage, which is suitable to monitor damage or infestations in agricultural crops and forests.

For detailed planning and execution of data acquisition it is mandatory to have direct access to geostationary systems such as Meteosat second and third generation (MSG, MTG) and GOES-East/West to estimate the actual cloud coverage.

5. EnMAP perspectives and impact

Accurate, quantitative information on the state and evolution of terrestrial and aquatic ecosystems is needed to support resource management, conservation strategies, rehabilitation measures, and ecosystem services. Hyperspectral image analysis can support a wide range of environmental applications ranging from the assessment of vegetation state, mineral assemblages, water constituents and environmental hazards. The EnMAP Core Science Team identified some of the most challenging environmental issues, to which EnMAP can contribute. These issues were grouped into five major environmental themes, namely Terrestrial Ecosystems, Aquatic Ecosystems, Natural Resource Management, Hazards and Risks, and Atmospheric Research and are presented in section 2.3. Addressing these environmental issues requires interdisciplinary approaches across the Earth's spheres (i.e., biosphere, hydrosphere, pedosphere, lithosphere, atmosphere and anthroposphere), because they are interconnected by various links and interactions (Figure 5). Fluxes of energy, water, carbon and sediment affect multiple spheres through complex feedback mechanisms and can be assessed by direct and indirect means with imaging spectroscopy. The following sections provide an overview of the relevance, the current lines of research, and the potential contribution of EnMAP for each of the five major environmental themes.

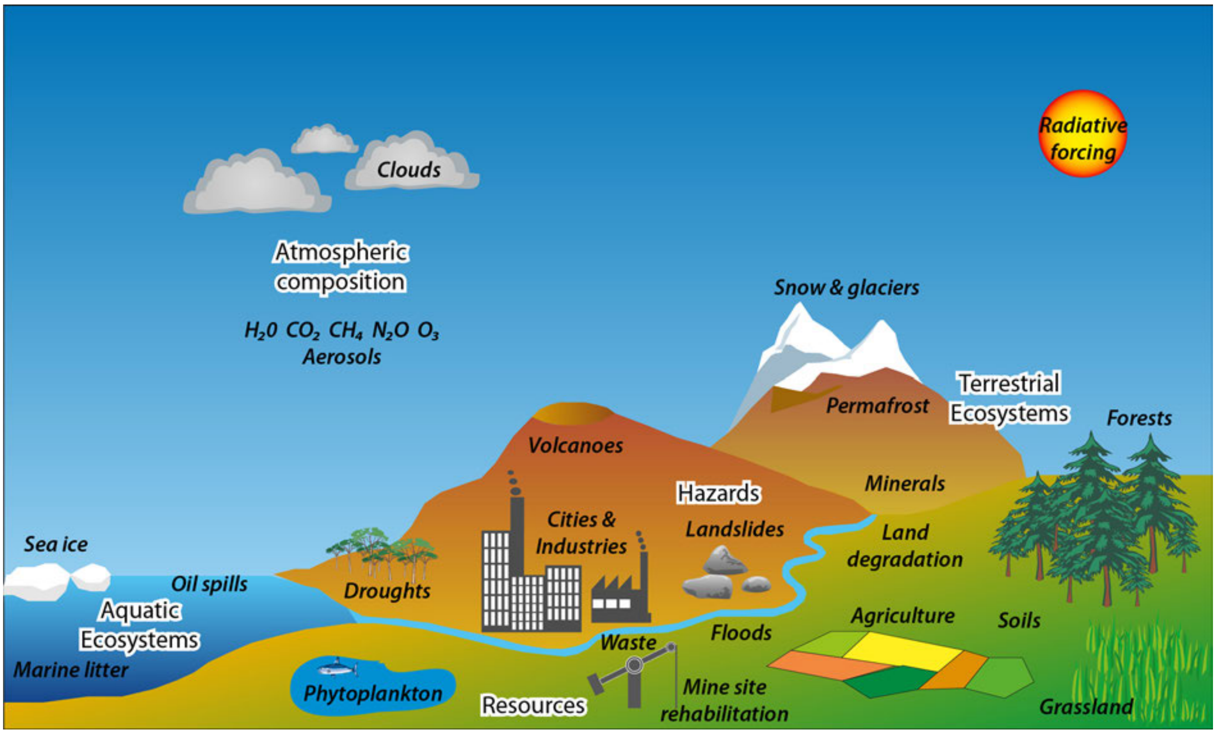

Figure 5: Major research themes and associated application areas for imaging spectroscopy

5.1 Terrestrial Ecosystems

5.1.1 Natural ecosystems and ecological gradients

Pristine ecosystems on Earth are scarce (*Kareiva et al.*, 2007) and global environmental change impacts even remote areas of our planet. We here refer to ecosystems that are largely untouched by human land use and unmanaged or protected. Sharp ecosystem boundaries are mostly a characteristic of managed ecosystems and therefore transitions or ecological gradients between different natural or natural and managed ecosystems are also considered here.

Specifically, monitoring and better characterizing natural or close to natural vegetation is essential to support sustainability of human-environment systems from local to global scales. Moreover, analysing and monitoring processes related to unmanaged land are crucial to deepen our understanding of indirect global environmental impacts and help to improve environmental models.

Quantifying ecosystem characteristics and the services they provide requires using information at the meso- to macro-scale, which needs to be consistent and reproducible through space and time. Such information can only be obtained by means of remote sensing (*Defries et al.*, 2005). EnMAP data and products derived from it will overcome current limitations, particularly in respect to the quantification of complex processes and gradual changes, which are prevalent in natural ecosystems (*Asner et al.*, 2005). Concepts for the description of heterogeneous vegetated surfaces and floristic composition become possible, e.g. the plant functional types concept (*Lavorel et al.*, 2011).

Previous studies made use of field-based or airborne hyperspectral imagery for quantifying biophysical parameters of natural vegetation, such as primary production, Leaf Area Index or photosynthetic activity (*Lee et al.*, 2004; *Smith et al.*, 2002), biomass (*Mutanga and Skidmore*, 2004; *Cho et al.*, 2007), carbon storage and water fluxes (*Fuentes et al.*, 2006), ecosystem structure (*Asner et al.*, 2005), or vegetation successional stage (*Oldeland et al.*, 2010). Further uses of hyperspectral imagery have been on single species mapping (*Cochrane*, 2000; *Clark et al.*, 2005) and the monitoring of invasive species (*Underwood et al.*, 2003). However, most of these studies are limited to one acquisition per year or less and none of them could make use of high quality, landscape scale hyperspectral data, as EnMAP will provide. While the relatively coarse spatial resolution of hyperspectral satellite data will add challenges to such applications, data quality and availability will open up new pathways for parameter retrieval.

In this sense, high temporal and systematic coverage by hyperspectral satellite systems such as EnMAP will allow for continuous monitoring of natural processes, as demonstrated by pilot studies using data from experimental spaceborne systems (*Asner et al.*, 2004; *Stagakis et al.*, 2010), and will thus improve our understanding of these processes (*Ustin et al.*, 2004). Phenological studies, previously based on existing platforms (*Hoare and Frost*, 2004; *Fisher et al.*, 2006), are likely to reveal new insights by improved information that can be retrieved from high spectral resolution data. These data should be fundamental in improving existing carbon emission accounts and monitoring efforts (*Numata et al.*, 2011), necessary to make mechanisms, such as REDD or REDD+, effective.

Physical-based modelling concepts are not advantageous for the work in natural environments because model calibration of such heterogeneously composed vegetated surfaces is too complex. Advances in statistical and machine learning, however, provide a set of methods that are capable of coupling qualitative and quantitative analysis without being affected by collinearity effects in contagious datasets. Such new developments like self-learning decision trees, partial least square regressions, Gaussian processes or support/import vector machines (*Breiman*, 2001; *Helland*, 1990; *Vapnik*, 1998; *Zhu and T.*, 2005) have high potential in making best use of the extended information in EnMAP data and allow for describing mentioned processes (e.g. *Verrelst et al.*, 2012; *Feilhauer et al.*, 2010).

Beyond the direct use of such generic algorithms for empirical modelling approaches, the generation of new indices and thematic transformations is of utmost importance. Multi-band indices and non-linear transformations may be developed based on insights derived from empirical studies with, for example, a non-linear kernel-based approach. Such developments have to be robust and possibly general. However, in most cases a biome-specific calibration procedure will be required and such calibration will be a key aspect in algorithm development in near future.

EnMAP imagery will thus be extremely useful for monitoring natural ecosystems and their services, by allowing the accurate quantification of gradual biophysical parameters, and the description of heterogeneous landscapes through the estimation of natural composition and pixel fractions of cover.

The following main scientific tasks are related to natural ecosystems:

- Assess *ecosystems services*, such as the above ground *carbon sequestration potential*;
- Retrieve biochemical and biophysical parameters as input in ecosystem and species habitat models to improve the understanding of *ecosystems and ecological processes*;
- Assess the spatial pattern of *ecosystems and biodiversity distributions* from local to global scales in the context of nature protection legislation such as the European habitats directive;
- Monitor *natural or quasi-natural vegetation areas* (such as nature protection areas, naturalized, un-used or extensively used areas) to understand causes and driving forces of changes, for example, in the context of land abandonment, forest disturbance or land degradation processes in order to combat biodiversity loss and promote ecosystem stability (e.g. REDD+);
- Quantify spatial and temporal *ecosystem transitions*, such as e.g. vegetation succession, habitat heterogeneity, plant or animal community transitions, and assess potential feedback mechanisms; and
- Investigate the effect of climate change and other anthropogenic and non-anthropogenic forces on *global vegetation gradients*.

5.1.2 Forests

Worldwide, forests provide timber and non-timber products as well as numerous environmental goods and services, such as conservation of biological diversity and climatic control, which are crucial for local livelihoods (*FAO*, 2010). However, forests and forested ecosystems are being rapidly depleted and under increasing pressure due to global warming (*Birdsey and Pan*, 2011; *Peng et al.*, 2011) and expanding human populations and economies (*Hansen et al.*, 2008). Deforestation associated with conversion of forests to agricultural land, legal and illegal timber harvesting and recurrent wildfires are some of the most important processes, which affect forested landscapes (*Bond*, 2010).

The challenges in forest management are multiscale and intricately linked to society's needs to preserve multiple forest values and benefit from its products. The pressing need for sustainable forest management aims at combining economic interests with ecologic concerns. In this context, remote sensing data serve economically oriented assessments and management needs as well as studies of ecological processes and functions (*Franklin*, 2001). Applications of remote sensing contributing to sustainable forest management are generally presented in four categories that include classification of forest covertype (i.e. tree species), estimation of forest structure and available resources (i.e. timber volume, height, age, crown closure), forest change detection and forest modelling. For each category measurable indicators are needed to quantify the effects of management activities and natural phenomena on the sustainability of forest resources. Current research is directed at quantitatively relating remotely sensed spectral information to ground-based assessments of structural and physiological aspects of forest condition.

The future EnMAP satellite can efficiently characterize the spatial distribution of forest ecosystems and provide an inventory of forest resources. Such inventories typically comprise quantitative attributes related to forest species, health, and functioning, including estimates of chlorophyll, nitrogen, lignin and canopy water content (*Goodenough et al.*, 2003a; *Matson et al.*, 1994; *Schlerf et al.*, 2005, 2010). Quantifying such species-specific canopy biochemistry differences is well established to map forest species and ecosystems (*Goodenough et al.*, 2003b; *Martin et al.*, 1998). The fusion of hyperspectral data with other remote sensing data sources like Radar or Lidar offers additional perspectives to estimate forest structure, forest type, biomass, timber volume, tree heights, stem densities, and age classes (*Anderson et al.*, 2008; *Dalponte et al.*, 2008; *Huang et al.*, 2007; *Hyde et al.*, 2006). Furthermore, it is possible to estimate the above ground carbon stored in the forests, e.g. in the context of REDD (UN Collaborative Initiative on Reducing Emissions from Deforestation and Forest Degradation, FAO, UNDP, UNEP *Framework-Document*, 2008), by combining hyperspectral imagery with geographic information, field calibrations and physiological models (*le Maire et al.*, 2005), as well as texture and object information (*Blaschke*, 2010; *Buddenbaum et al.*, 2005; *van der Linden et al.*, 2007). Thus, imaging spectroscopy offers accurate ways of providing needed forestry information as well as the potential for new indicators of vegetation state and indices of forest biochemistry and functioning.

Reforestation, afforestation, and deforestation rates can be assessed on regional scales (*Clark et al.*, 2011; *Goodenough et al.*, 1998). Such measures are needed for the Kyoto Protocol on greenhouse gas reductions and provide an essential contribution for documenting changes in the forests over time. Previous studies on forest ecosystems emphasized the role of imaging spectroscopy allowing detailed and accurate retrievals of relevant vegetation properties (*Ollinger and Smith*, 2005; *Schaepman et al.*, 2004), where the most important vegetation parameters are leaf chlorophyll and nitrogen content, the fractions of photosynthetically absorbed radiation (fAPAR), canopy water content, annual maximum leaf mass per area (LMA), and annual maximum leaf area (LAI) (e.g. *le Maire et al.*, 2008). Finally, EnMAP can estimate changes in forest structure and condition, including above ground carbon stocks at improved accuracies.

Important ecological processes in forests include carbon exchange (photosynthesis and respiration), evapotranspiration, and nutrient cycling (*Coops et al.*, 2009; *Waring and Running*, 2007). To model these processes on a regional to global scale, imaging spectroscopy currently provides accurate local estimates of forest structural and chemical properties, which serve as required inputs to initialize, calibrate, and validate such models (*Tenhunen et al.*, 1998). In the mid-term perspective these models can assist management decisions to mitigate the effects of climate change on a regional scale.

Given the complexity of hyperspectral analysis, expert systems to support the analysis for EnMAP data have been developed (*Goodenough et al.*, 2012, 2007). Forest reflectance models, as compared to agricultural models, require much greater attention to forest structure, clumping, shadowing and understory effects. Reflectance models ranging from simple approaches like INFORM (*Atzberger*, 2000) or 4-scale (*Chen and Leblanc*, 1997) to more complex geometric-optical radiative transfer models like FRT (*Kuusk and Nilson*, 2009) or raytracing models like FLIGHT (*Gerard and North*, 1997) have been developed and validated in order to analyse the complex hyperspectral signal of forests (*Foerster et al.*, 2010). Despite some successful attempts (*Combal et al.*, 2002; *Koetz et al.*, 2004; *Schlerf and Atzberger*, 2006; *White et al.*, 2000), the inversion of these models is still a challenge and a pressing research issue for the next years.

EnMAP will be evaluated as a tool for developing spectral indices that will serve as bio-indicators of forest condition. Through repetitive sampling of selected forest condition test sites, EnMAP would add the phenological history to the full spectral sampling data to yield effective bio-indicators of forest condition. EnMAP will provide a capability to compare observations of spectral properties of forests in many different countries. This is essential in order to develop a consistent tool for monitoring the carbon state of the world's forests and their response to climate change. Frequent and broad coverage will increase our understanding of the links between pigments, canopy chemistry, stress, and forest type. For forest inventory programs, hyperspectral data from EnMAP can provide an important sampling system to ensure precise measurements of indicators for a sustainable development.

Accordingly, the following main scientific tasks are considered important in regard to forest applications:

- Map forest *species distributions* using hyperspectral, fused and multitemporal datasets, exploring the potential of advanced classification algorithms, texture and object information, and linkages to geographic databases etc.;
- Estimate *forest biomass* and above ground carbon;
- Assimilate biochemical and structural *forest parameters* into process models;
- Enhance and develop *invertible vegetation canopy reflectance models* for the forest environment, extraction of forest parameters, and forest mensuration, health, and risk assessment;
- Investigate the viability of *phenological signatures* through indicators of canopy pigments and chemistry with regard to ecophysiological processes;
- Develop improved optical indices that will serve as *bio-indicators of forest condition*;
- Develop forest monitoring procedures including multi-temporal and multi-sensor data for the detection of changes in *forest quality and canopy cover,* and
- Create advanced expert systems to improve the efficiency of hyperspectral information extraction within the forestry context.

5.1.3 Cryospheric ecosystems

The magnitude of predicted global warming is largest in high latitude and high altitude regions (*IPCC*, 2007). Retreating glaciers, decreasing sea ice extent, shorter snow cover periods, and accelerated degradation of permafrost areas testify this longstanding trend (e.g. *Pritchard et al.*, 2009; *Liston and Hiemstra*, 2011; *Stroeve et al.*, 2007; *Lawrence and Slater*, 2005). Complex feedback mechanisms caused by a decrease in surface albedo imply a wide range of climatic, hydrologic, ecologic, and geomorphic changes in these regions. Yet, quantifying the state and changes of snow, glaciers, ice caps, sea ice and permafrost is strongly hampered by missing ground observations due to the challenging logistics as a result of the remote and complex terrain. Therefore, satellite observations represent a unique database to track and quantify variations in the cryosphere.

Despite the environmental limitations for optical sensors in the polar regions (i.e. months of polar night, high cloud coverage, and year-round low solar incidence angle) hyperspectral data provide unique information on biogeochemical parameters that are important to model energy, water, sediment, and carbon fluxes. Therefore, hyperspectral remote sensing offers the great potential to measure key diagnostic parameters that verify changes in the cryosphere at landscape scales.

Permafrost

Permafrost covers about 25% of the northern hemispheric land area and hence represents one of the largest components of the Arctic cryosphere. Arctic environments maintain important ecosystems with unique plant communities, which are particularly sensitive and responsive to climatic changes. Field observations of the active layer (top layer of soil that thaws during the summer) and the permafrost dating back to the 1970s show a continuously warming trend with a high spatial variability in warming rates that depend on ice content and absolute ground temperatures (*Smith et al.*, 2010; *Romanovsky et al.*, 2010). Large-scale permafrost degradation may provoke feedbacks such as activation of the soil carbon pool and a northward expansion of shrubs and forests (*Lawrence and Slater*, 2005). Increased permafrost knowledge is particularly important for the design and maintenance of infrastructure in permafrost environments and for designing effective adaptation strategies for the local communities under warmer climatic conditions (*Romanovsky et al.*, 2010).

Permafrost is an underground thermal phenomenon, which cannot be directly observed by optical remote sensing. However, there is a large number of surface indicators suited for hyperspectral remote sensing applications, such as changes in vegetation biomass and communities, surface morphology, hydrology, and aquatic ecosystems. In particular, the discrimination of different vegetation types and biophysical variables (e.g., leaf area index or biomass) is of great interest in tundra/permafrost research (*Rees et al.*, 2003; *Laidler and Treitz*, 2003; *Hope et al.*, 2003). Similarly, robust data on the proportions of soil, nonphotosynthetic vegetation and green vegetation in various landscapes are needed (*Warner and Asada*, 2006). For example, *Muster et al.* (2012) used CHRIS and other optical remote sensing data to investigate the water body area and the moisture regime for detailed process studies of energy and water fluxes in the Lena Delta of Siberia. Detailed spatial information on surface variables, such as vegetation biomass, plant functional types, the moisture regime, the insulating moss layer, the surface water ratio, the dissolved organic carbon and particulate matter concentration, is crucial to detect the state of permafrost and to model thermal, hydrological, and carbon fluxes.

Snow & Ice

Characterization of snow-covered areas and glaciers is critical for understanding Earth's hydrology, climatology and ecology because of their significant effect on the energy balance at the land-atmosphere boundary and their importance as fresh water sources. However, detailed ground-based measurements of snow and glacial properties are scarce due to the remoteness and complex terrain of most snow-covered areas. Imaging spectroscopy can be used to retrieve key snow parameters, such as snow covered area, albedo, grain size, snow impurities, and liquid water content in the near-surface layer, in order to model their effects on the regional water and energy cycle (*Dozier and Painter*, 2004).

Snow evolves after its deposition. Snow albedo and snowmelt are directly linked to the growth of grain size (*Warren and Wiscombe*, 1980). The broadband reflectance decreases dramatically, especially in the near infrared range, as the snow grains evolve. In the same way liquid water inclusions of melting snow yield albedo reductions, because liquid water in snow caused the grains to form clusters (*Colbeck*, 1979). Similarly, snow contaminants such as dust, algae, and soot degrade snow reflectance significantly, especially in the visible spectrum by adsorption of incoming radiation and at longer wavelength by increases in grain size through local microscale metamorphism (*Dozier et al.*, 2009). Repeated hyperspectral measurements of snow cover enable us to quantify the evolution of broadband albedo by accounting for various effects like grain size and snow contaminants. In addition, spectral mixture analysis enables mapping surface constituents at subpixel resolution in order to accurately represent the spatial distribution of snow (*Nolin et al.*, 1993). Accurate measurements of these physical snow properties (i.e. fractional snow covered area and snow albedo) are prerequisites to drive distributed hydrological models in order to quantify timing and magnitude of snowmelt runoff and its source areas.

Future snow and ice research will benefit from a synergistic data collection that combines fine spectral and spatial resolution (EnMAP) with a broad swath and daily coverage of the whole Earth (MODIS, Sentinel 3, VIIRS). Envisioned applications include regular tests of medium spatial resolution data with EnMAP and data assimilations to improve models of snow cover and albedo evolution by an increased temporal and spatial resolution. Earth observing imaging spectrometers have large potential to capture seasonal variations in snow cover and albedo with high accuracy. Further information that may be retrieved from EnMAP data include snow grain size, liquid water near the surface and snow impurities content derived from dust, soot, or organic content. Some of the remaining challenges are to improve snow mapping in forests, adapt to angular variability in the signal, further investigate the measurement and consequences of absorbing impurities in snow. This information from both operational sensors and imaging spectrometers need to be incorporated into hydrologic models that, together with advances in modelling and remote sensing, would better characterize the fluxes and reservoirs in snow covered areas (*Dozier et al.*, 2009).

Imaging spectroscopy of sea ice and glaciers can similarly contribute to an improved understanding of surface energy fluxes and mass flux quantifications. For example, the extent of melt ponds on sea ice and glaciers can be quantified and their resulting impact on the surface albedo. Furthermore, the extensive glacial debris cover, which characterizes most mountain glaciers, can be analysed by spectroscopic means to decipher their origin and to improve glacial mapping as well as our understanding of glacial ablation and kinematics (*Casey et al.*, 2012).

The following main scientific tasks are related to cryospheric ecosystems:

- Assess the state and changes in *vegetation biomass, hydrology, and surface morphology* in permafrost landscapes;
- Discriminate different permafrost vegetation communities and plant functional types;
- Develop and improve new hyperspectral approaches to retrieve *snow properties* (e.g., albedo, grain size and near-surface liquid water, mineral and organic contaminants) and *spatial snow cover distribution*;
- Establish multi-seasonal time series of snow parameters to improve regional *hydrologic models*;
- Analyse the effect of *snow impurities* on variations in snow melt timing and magnitude; and
- Explore *synergies to multispectral sensors* with varying spatial scales to improve snow mapping in forests and adapt to angular variability.

5.1.4 Agricultural land

Limited land resources, increasing land degradation, rising population numbers, an increasingly meat-prone diet, a growing demand for biofuels, and on-going climatic change coupled with more frequent extreme events cause substantial land use conflicts between food- and energy production versus ecosystem services including biodiversity conservation. To sustain the benefits of natural ecosystems, a growing demand for agricultural commodities can only be met by sustainable increases in land productivity. However, global scale studies highlight that large appropriation of land resources contrast low efficiencies in land management (e.g. water use) (*Haberl et al.*, 2007; *Kijne et al.*, 2009). The challenge to reverse this global trend involves a wide range of land management aspects, including the selection of suitable plants and cultivars, water productivity, organic farming, fertilizer and pesticide management, soil conservation, and irrigation. Because of the spatial variability in climate, soils and topography, as well as societal aspects like culture, education, technology and markets, agricultural management relies critically on spatial data to support management decisions. Therefore, modern farming practices try to incorporate the identification, analysis, and management of spatial and temporal variability within regions and fields for optimum profitability, sustainability, and protection of the environment.

Moran et al. (1997) identified key areas where remote sensing can provide critical spatial information for agricultural management. These aspects include the mapping of crop yield and biomass as well as the monitoring of seasonally and spatially variable soil and crop characteristics. Since this early assessment, our understanding of farming related land heterogeneity management has progressed towards a site-specific management to support sustainable productivity. This method for agricultural management includes early detection of infections, as well as water and fertilizer deficits, monitoring of ecological intensification of extensive agriculture as well as ecological extensification of intensive agriculture, and the identification and evaluation of new land reserves where agriculture could be established due to climatic changes. These land management practices lead to a new demand for more complex and integrated global information, e.g. in land evaluation, site and plant specific yield gap (the difference between potential and actual yield) determination, fertilizer intensity monitoring as well as determination of seeding dates and spatially distributed plant phenology.

Hyperspectral instruments, providing agricultural information more accurately and in more detail than existing operational multispectral sensors, can substantially support farming decisions (*Staenz et al.*, 1998). In addition, hyperspectral instruments offer more spatially distributed, in-depth information than provided by conventional statistical regression analysis between laborious ground-truth measurements of vegetation parameters and simple spectral indices. A more thorough approach is to fully exploit the complete spectral information content by invertible vegetation canopy reflectance models. These models infer biochemical/biophysical parameters, such as chlorophyll and water content, from continuous canopy spectral reflectance signatures and have previously been applied to field crops and grasslands (*Bach et al.*, 2003, 2011; *Jacquemoud et al.*, 2000; *Migdall et al.*, 2009, 2010; *Verhoef and Bach*, 2003). The parameters that control productivity and health of vegetation can be estimated through model inversion using remote optical measurements such as retrieved from EnMAP.

Recent studies have shown that the following set of crop parameters relevant for agricultural production can be retrieved from hyperspectral data:

- Leaf area index (LAI) describing the size of the producing layer (*Weiss et al.*, 2001);
- Absorbed photosynthetic active radiation (APAR) providing the amount of absorbed energy usable for production (*Weiss et al.*, 2010);
- Chlorophyll content as the chemical actor for photosynthesis, which is dependent on nitrogen application (*Haboudane et al.*, 2002; *Oppelt and Mauser*, 2003);
- Water content as indicator for water status of a specific crop type and its maturity (*Ceccato et al.*, 2001; *Champagne et al.*, 2003);
- Plant density as indicator of disease sensitivity (*Larsolle and Hamid Muhammed*, 2007);
- Plant pigments such as carotinoids and anthocyanins as indicators of adaptation of the canopy to varying light conditions (*Blackburn*, 2007).

Assimilation of these and additional remotely sensed plant parameters, like phenology and seeding date, into agro-ecological models allows to explicitly simulate crop growth for each pixel based on the plant parameters retrieved from hyperspectral remote sensing data. This approach provides site-specific information on key farming parameters like biomass, plant height, crop yield, nitrogen or phosphorus deficit and/or uptake, which are not directly observable with remote sensing. Furthermore, time series of remotely sensed plant parameters account for spatiotemporal heterogeneity in agricultural production models, which can also be used to explore the suitability of different management options (*Hank et al.*, 2012).

From the large number of existing crop growth models, the CERES family (*Ritchie and Otter*, 1985) is one of the most prominent models, which relies on statistical relationships between environmental variables and plant growth and development. PROMET-V (*Schneider and Mauser*, 2001) is an advancement of such an agricultural model towards spatially distributed simulations that integrate remote sensing data.

A further development towards process understanding is achieved by dynamic vegetation models, which simulate plant growth on the basis of eco-physiological processes and feedbacks during the photosynthesis and respiration process.

Currently, the most realistic representation of vegetation dynamics in regional agro-ecological models as well as regional to global ecosystem and Earth system models is based on the combination of dynamic vegetation models, agricultural management models (e.g. PROMET (*Hank*, 2008), LPJ-mL (*Bondeau et al.*, 2007)), and appropriate canopy models that simulate the distribution of assimilates among the plant constituents (i.e. roots, stem, leaves) in order to allow for a realistic representation of complex canopy layers. Recent studies have shown that the proposed data assimilation approach is viable and provides reasonable results (*Bach et al.*, 2003; *Weiss et al.*, 2001; *Hank et al.*, 2012). Nevertheless, further research and development is needed to improve models, in particular with regard to process representation and accuracy. In addition, various data assimilation methods should be tested under a broad range of farming conditions, especially in regions with low-efficiency farming systems, different crop (e.g. cassava, sorghum, groundnut) and energy plants (e.g. sugar cane, oil palm, jatropha), different stresses (e.g. water, fertilizer, temperature), irrigated agriculture, and mixed silvi-agricultural systems in order to reach an operational stage of such coupled model systems.

Besides further improvements in modelling approaches, sophisticated agricultural applications need to be based on frequently available hyperspectral imagery with high data quality standards. Based on the knowledge already gained in numerous studies with airborne sensors, EnMAP will offer hyperspectral data in a suitable spatial and temporal resolution to approach the next major scientific step from regression analysis to a mechanistic process representation.

The following major scientific and application tasks have been identified in agriculture:

- Develop and improve accurate, robust and reliable *crop parameter retrieval* methodologies based on inversion of improved canopy reflectance models using imaging spectroscopy data (retrieval of crop type, LAI, APAR, chlorophyll content, plant water content, canopy geometrical structure);
- Develop and improve methods for quantitative mapping of *soil parameters*, also taking the spectral signal of vegetation into account;
- Develop and improve approaches to derive *complex canopy parameters*, e.g. crop phenology, management intensity or yield gap, from hyperspectral remote sensing data, in conjunction with ancillary remote sensing data.
- Develop operational methodologies for *yield and biomass estimation and forecasting* based on EnMAP and ancillary data.
- Map crop *species distribution* using hyperspectral-temporal information content;
- Distinguish *crop stressors* like nitrogen deficiency, crop disease, insect infestation, water stress, and chlorosis; and
- Develop and improve approaches to assimilate remote sensing derived spatial distributions of vegetation and soil parameters into dynamic *agro-ecological models*.

5.1.5 Urban areas

Over the past 50 years, anthropogenic ecosystem changes were more rapid and extensive than in any comparable period of time in history (*MEA*, 2005). The world currently experiences rapid urbanization and an increase in the number of megacities, particularly in developing countries. According to the

United Nations Development Program, urban population growth will continue to rise substantially over the next several decades (*UN*, 2006). The (often uncontrolled) process of urbanization always results in changes in land use and cover and causes serious problems such as environmental pollutions, destruction of ecosystems, waste disposal and others. Moreover, urbanization and related changes in lifestyle increase the per capita demand for energy, goods and services (*Meyerson et al.*, 2007). Land conversions, introduced by urban consumption patterns, have regional consequences for the biophysical system that may lead to global consequences (*Sanchez-Rodriguez et al.*, 2005). Thus, there is a critical need to map urban land cover composition and monitor urban growth. Remote sensing techniques are widely used to study urban environments. However, hyperspectral applications are comparably scarce (*Xu and Gong*, 2007; *Cavalli et al.*, 2008; *Weng et al.*, 2008), which may, to a great extent, be explained by the spectral and structural complexity of urban areas (*Small*, 2003, 2001; *van der Linden and Hostert*, 2009) and to a limited availability of appropriate sensors covering the full reflective wavelength range. EnMAP hyperspectral data of medium spatial resolution will open up new opportunities to describe and monitor land cover composition in urban areas and along urban-suburban gradients assisting in the understanding of the dynamics of global urbanization (*Heldens et al.*, 2011).

Classification schemes for urban areas are generally influenced by the spatial scale of analysis and the scope of related studies (e.g. *Heiden et al.*, 2007; *Herold et al.*, 2004). Research is needed to determine the most suitable classification scheme for EnMAP. Given the 30 m ground sampling distance of EnMAP urban mapping will often require a quantification of the sub-pixel land cover composition. For these types of analyses, techniques such as spectral unmixing or regression modelling that are capable of dealing with the spectral variety of urban surfaces have to be developed (*Roessner et al.*, 2001; *Franke et al.*, 2009). For both qualitative and quantitative analyses of urban areas the implementation of reference spectral libraries is essential (*Heldens et al.*, 2011), yet poses a challenging step that requires extensive collaboration between international research groups (*Hueni et al.*, 2009; *Rasaiah et al.*, 2011). The combination of medium spatial resolution and high spectral information content requires new concepts for the description of land cover composition. While the occurrences of spectrally pure surface materials are rare, urban spectral mixtures contain compositional information that might be characteristic for certain urban structures such as inner city centres or commercial areas. Recent studies that focused on plant species variations used compositional variation to extract major vegetation gradients (*Schmidtlein and Sassin*, 2004; *Feilhauer et al.*, 2011). Applying such concepts to urban areas could account for the spectral and spatial information content of EnMAP data of urban areas.

One essential application with regard to urban planning is reliable mapping of imperviousness. Here, approaches that combine qualitative and quantitative analyses appear most suited to make full use of the additional information from EnMAP data. This additional information will help make approaches based on the V-I-S concept (*Ridd*, 1995; *Wu and Murray*, 2003; *Lu and Weng*, 2006) more reliable or help to extend such models by additionally differentiating built-up and non-built-up areas. Reliable surface material indicators are needed for applications such as urban climate studies. In this context, fusion of spectral and thermal data (at the feature or knowledge level) may reveal the relationship between thermal patterns, urban surface materials, and urban structure and thus, helps to understand their influences on the urban climate (*Oke*, 1988). Such data fusion studies have already been carried out at local scale with airborne thermal and hyperspectral data (e.g. *Xu et al.*, 2008). Novel fusion techniques combining future EnMAP data with thermal sensors (e.g., ASTER, HyspIRI) can open up new opportunities for urban climate studies on larger scales. Another challenging task is the combined analysis of hyperspectral data and high-resolution remote sensing data, which enables a detailed analysis of urban structures combined with surface material information. In this context, image data fusion (*Zhang*, 2010) is a promising technique to retrieve further information from EnMAP data. Yet, methodological gaps exist for spatial upscaling techniques that preserve spectral information content. Overall, the synergistic use of hyperspectral-, thermal-, and optical data with advanced data analysis techniques may result in enhanced socioeconomic and environmental indicators to model urban dynamics and their social and environmental consequences.

Accordingly, main scientific tasks related to urban areas include:

- Map and monitor *urbanization* and its dynamics on a global scale;
- Implement a comprehensive *spectral library* to analyse urban land cover based on EnMAP data;
- Develop and improving classification algorithms to *map urban land cover* (including classes that are spectrally ambiguous in multispectral data) at the spatial resolution of EnMAP;
- Develop algorithms for quantitative analysis of *urban land cover composition* at the spatial resolution of EnMAP with regard to mixed pixel problems and rare pure endmember availability;
- Investigate of new concepts for the information extraction based on compositional information of spectral mixtures;
- Apply the V-I-S concept to monitor *impervious surface fractions*, e.g. in context of urban climate studies;
- Support *urban climate* studies by hyperspectral data; and
- Map the abundance of *hazardous materials* such as asbestos, e.g. in the context of risk analyses.

5.2 Aquatic Ecosystems

5.2.1 Coastal and inland water

Coastal and inland water bodies are vital for recreation, food supply, commerce and human health, and they also support habitats for a large floral and faunal diversity. Currently, these ecosystems experience high pressure from increasing social and economic human activities as well as climate change. As sinks for pollutants, coastal and freshwater ecosystems are among the most sensitive indicators of environmental impacts related to human activities (*UNEP*, 2012). For example, a major global ecological problem is the increasing eutrophication and pollution of coastal and inland water bodies caused by fluvially transported substances such as phosphate and nitrogen compounds, which derive from intensified agricultural and industrial activities. Monitoring and managing the water quality of coastal and inland habitats is necessary as they are vital to many kinds of utilization, including urbanisation, tourism, transportation, industry, fish farming and drinking water supply. According to the EU Water Framework directive 2000, specified biological, hydro-morphological and physico-chemical parameters of water bodies have to be monitored on a regular basis.

A major advantage of hyperspectral data covering coastal and shallow freshwater bodies is the ability to spectrally unmix various in-column optical constituents and the sea floor or lake bottom (*Carder et al.*, 1993; *Goetz*, 2011). The advanced spectral resolution of EnMAP in the visible and near-infrared region will allow the assessment of water constituents including phytoplankton pigments, suspended matter, dissolved organic matter, dissolved organic carbon concentration, and water transparency. Moreover, phytoplankton taxonomic groups can be identified, which provide indications for the occurrence of harmful algal blooms (*Bracher et al.*, 2009). Chlorophyll-a concentration is widely used as an indicator of algal biomass that depends upon nitrogen and phosphate availability in the water bodies (*Carlson and Simpson*, 1996; *Kamarainen et al.*, 2009). Water transparency is a widely used indicator of the trophic state, which is influenced by the abundance of organic and inorganic suspended particulate and dissolved matter

(*Kirk*, 1994). Several researchers have developed algorithms to quantify various parameters, such as chlorophyll-a, humic substances, suspended matter, yellow substances, and water transparency (*Giardino et al.*, 2007; *Kallio et al.*, 2001; *Schiller and Doerffer*, 1999; *Thiemann and Kaufmann*, 2000, 2002). EnMAP can make use of these standards for detailed observations of coastal zones and inland waters, while sensors such as MERIS, MODIS and SeaWIFS are designed for ocean applications with frequent observations at coarser spatial resolutions. Algorithms for coastal and inland water constituents with different phytoplankton, particulate and dissolved matter composition will be adapted and improved for EnMAP to provide water quality data at a higher spatial resolution. Water quality assessment serves both monitoring of freshwater security and the still increasing importance of aquaculturally used coastal and inland water bodies. Moreover, water quality assessment is crucial for the monitoring and management of endangered ecosystems such as coral reefs, seagrass meadows or mangrove forests (*Bell et al.*, 2008; *Landvelde and Prins*, 2007).

EnMAP data will not only offer more frequent observations of in-column constituents, but will provide frequent information about the type and status of the sea floor substrate and its changes. Water column correction approaches using hyperspectral data allow the identification of bottom vegetation types and, if regularly monitored, the observation of sedimentation dynamics (Deronde et al. 2004) as well as short- and long-term changes in species distribution and structure (*Vahtmaee et al.*, 2011). Quantitative analyses of coastal benthic communities enable the investigation of net primary production (*Dierssen et al.*, 2010). Moreover, many benthic species act as environmental indicators. Their frequent monitoring therefore enables an estimate of the state of coastal marine environments and provides evidence for environmental changes (*Phinn et al.*, 2003; *Vahtmaee et al.*, 2006). In this context, the fusion of EnMAP data and satellite data with a high geometric resolution (e.g. Worldview, GeoEye) offers the potential to pinpoint heterogeneously distributed vegetation and sediment patches. The monitoring of benthic vegetation can support integrated coastal zone management when species of certain genera (e.g. Ulva, Laminaria, seegrasses) are grown as a food supply for humans or aquaculture of marine animals (*Anderson et al.*, 2007; *Radiarta et al.*, 2011). The fusion with spatially high-resolution data also offers the potential to monitor frequently invasive benthic and emergent species (*Albright and Ode*, 2011; *Forrest et al.*, 2012).

Coastal ecosystems are highly productive and store large amounts of carbon (*Cole et al.*, 2007; *Pidgeon*, 2009). The distribution and dynamics of organic carbon in the vegetation, in combination with dissolved organic matter, are important in understanding regional and global carbon cycles. In this context, the EnMAP data provide efficient means to characterize the role of coastal and inland water bodies in carbon uptake and release.

Coastal and freshwater ecosystem management involves modelling and monitoring, which require a reliable information base and robust analytical techniques. Conventional mapping methods are logistically constrained, while airborne campaigns are cost intensive and often are limited to a few acquisition dates. The EnMAP satellite will enable a repeatable quantitative monitoring of the water-related environmental parameters mentioned above. The combination of hyperspectral data with ecological or hydrological models, geographic information systems and in-situ measurements allows the development of advanced integrated management plans for coastal zones and catchments characterized by inland water bodies, wetlands or reservoirs (*Yang*, 2009; *Radiarta et al.*, 2011). The fusion of hyperspectral data with thermal infrared data offers additional perspectives to the analysis of the trophic state of coastal or freshwater ecosystems. A combination of EnMAP derived bathymetry with RADAR, LIDAR or Laser-scan data can be useful to derive underwater topography and morpho-dynamics of shallow water areas (*Pleskachevsky et al.*, 2011). Thus, imaging spectroscopy enables an accurate estimation of water quality and sea floor parameters. Moreover, it offers the potential for new and complementary indicators for the characterization of the state of coastal and inland water bodies.

Accordingly, the following main scientific tasks are related to coastal and inland water body applications:

- Improve the identification of different substances by their spectral characteristics, such as improved chlorophyll quantification, the differentiation between ecological important phytoplankton groups, and dissolved organic compounds;
- Enhance the identification of different fractions of suspended mineral and organic particles;
- Monitor the spatio-temporal dynamics and structure of shallow sea/lake bottom substrate (vegetation and sediment);
- Monitor the distribution patterns of invasive submersed and emergent algae;
- Monitor the variety of algal species/genera in space and time as a bio-indicator of coastal and freshwater ecology;
- Monitor and taxonomically identify (potentially toxic) algal and phytoplankton blooms in eutrophicated coastal and inland waters;
- Estimate processes such as primary production in inland and coastal waters and suspended matter transport and its impact on coastal ecosystems;
- Monitor the distribution of sediments in tidal flats, wetlands, and mangrove forests; and
- Monitor coastal erosion and changes in coastal morphology.

5.2.2 Oceans

Oceans cover about 71% of the Earth's surface. Ocean currents greatly affect the Earth's climate by transferring heat from the tropics to the polar regions and influencing inland precipitation patterns. In general, oceans host a vast resource of marine life and play a vital part in the global carbon and oxygen cycle. For example, oceanic phytoplankton represent only 2% of the global plant biomass but is responsible for about 50 % of the global primary production (*Berger*, 1989).

Remote sensing enables us to study the upper ocean layer on various spatial scales to identify surface processes and to quantify characteristic parameters, such as phytoplankton biomass, sediment distributions, salinity, and surface temperatures. The first optical sensor built to study specifically the oceans, the Coastal Zone Color Scanner (CZCS), was launched in 1978 and paved the way for several subsequent instruments like SeaWIFS, MERIS, and MODIS and will be continued by OLCI in the forthcoming Sentinel series. All these globally covering multispectral instruments are optimised to analyse the open ocean, which can optically be characterised by only one parameter, the chlorophyll content (case 1 water). Since the advent of MERIS we are also able to resolve properties of optically more complex coastal waters (case 2) like chlorophyll, suspended sediments and chromophoric dissolved material (*IOCCG*, 2000). EnMAP's strength is based on its higher spectral and spatial resolution. These characteristics are important to resolve coastal regions with highly structured geographic features, infrastructures like rigs or offshore windfarms, and shallow waters with a high variability like lagoons, estuaries and wadden seas. For example, off-shore windfarms may affect sediment resuspension and may alter the biotic communities, which can be observed with hyperspectral imagery. Furthermore, it is of great interest to detect and analyse marine processes involving small-scale patterns and structures. An unresolved research topic in the marine community focuses on the detection of increased phytoplankton occurrences along eddy structures. Another open question that can be addressed with EnMAP concerns the dynamics of cyanobacteria blooms that develop along eddies and their linkage to the upwelling of nutrients along oceanic frontal and mixing zones.

The following main scientific tasks are related to ocean applications:

- Monitor the impact of off-shore windfarms on the bottom substrate and biotic communities; and
- Detect phytoplankton along small-scale eddy structures and quantify their dynamics.

5.3 Natural Resource Management

Natural resources are natural assets occurring in nature that can be used for economic production or consumption. Management of natural resources comprise their exploration, monitoring, and sustainable utilisation. Because natural resources form the basis for economic growth, they are of major interest for governments and industries. In this section, natural resources refer to the availability of abiotic resources including minerals, soils, and fossil fuels whereas biotic resources are mainly addressed in the previous section on "terrestrial and aquatic ecosystems" (see section 5.1 and 5.2). Imaging spectroscopy has proven to be an effective tool to detect, monitor, and manage natural resources. Current research focuses on the assessment of mineral deposits (e.g. *Clark et al.*, 2003), the management of mining impacts (e.g. *Swayze et al.*, 2000), and the deduction of soil properties (e.g. *Ben-Dor et al.*, 2009). Because most present studies are based on airborne hyperspectral imagery, EnMAP holds a considerable potential to expand lithospheric investigations and to monitor seasonal or event-based pedologic changes.

5.3.1 Resource investigations

Mineral mapping

Minerals are essential to an industrialized society. This particular interest in detecting mineral compositions has been the most significant driver in the development of spectroscopy (*Schaepman et al.*, 2009). Spectra of minerals exhibit several diagnostic absorption features mainly due to the presence or absence of transition metal ions (e.g. iron, chromium, cobalt and nickel) and molecular bonds (e.g. Fe-OH and Mg-OH in amphiboles, Al-OH in clay minerals, CO_3 in calcium carbonates). These specific absorption features facilitate regional mineral mapping based on imaging spectroscopy (*van der Meer et al.*, 2012; *Clark et al.*, 1990). Besides the mineral mining interest, mineral mapping can provide a better understanding of weathering, mineralization, hydrothermal alteration, and other geologic processes (*Clark et al.*, 2003; *Kaufmann et al.*, 1999). Detectable indicator minerals, such as kaolinite, dickite, alunite, sericite, chlorite and epidote, are commonly found in hydrothermal alteration systems that may contain deposits of economically valuable minerals, such as gold, silver and copper, to name a few. In this context, the detection and assessment of rare earth elements deposits are of greatest interest for both political relations and the global economy. In specific cases, subtle variations in chlorophyll concentration of homogeneous canopies may indicate heavy metal concentrations in the underground (*Collins et al.*, 1983). In addition to mineralogical investigations, lithospheric research includes the mapping of volcanoes and their plume composition (*Carn et al.*, 2005; *Guinness et al.*, 2007; *Spinetti et al.*, 2008).

Soil properties

Hyperspectral data as provided by the EnMAP satellite will hold considerable potential to characterize the pedosphere by identifying soil properties and their changes in time. In view of limited arable land area and rising population numbers, the emerging field of precision farming is receiving increased attention. Supported by imaging spectroscopy soil conditions can be assessed before, during, and after the growing season. In this way, farmers can better evaluate critical needs such as irrigation, nutrient supply, and cultivation to gain increased agricultural yields (*Dematte et al.*, 2000).

Soils are complex dynamic systems, which are formed and developed as a result of the combined effects of climate and biotic activities, and modified by topography. Soil development that can be either progressive or regressive with time modifies the chemical, physical, and mineralogical properties of soil surfaces to produce distinct spectral features that can be detected using high-resolution reflectance spectra (*Leone and Sommer*, 2000). In particular, the amount of organic matter and iron content, particle size distribution, clay mineralogy, water content, soil contamination, cation exchange capacity and calcium carbonate content, can be determined with imaging spectroscopy (*Ben-Dor et al.*, 2009).

Petroleum detection

Petroleum, or crude oil, consists of a complex mixture of hydrocarbons and other liquid organic compounds. Over the past decades, these hydrocarbons have been the primary energy source, which contributed significantly to technological and industrial advances. In recent years, there has been a growing demand for environmental monitoring, associated with the advance of petroleum exploration at deep offshore waters and oil sand extractions in pristine ecosystems. Imaging spectroscopy can be used to detect oil discharges on the Earth surface, which is of environmental concern and economical interest (*Lammoglia and de Souza Filho*, 2011). Oil seepages may occur naturally within onshore or offshore basins or result from leaks and spills during the extraction, transportation, storage, and utilization of petroleum. Oil pools and tar deposits can often be directly detected, whereas micro-seepages may give rise to vegetation stress or cause geochemical alterations in soil and rocks, which can be studied indirectly using hyperspectral sensors (*van der Meer et al.*, 2002).

Spectral characteristics of hydrocarbons are linked to their chemical composition, which can be used to distinguish various oil types such as crude oil, emulsified oil, and oil on ocean water (*Horig et al.*, 2001; *Lammoglia and de Souza Filho*, 2011). For example, hyperspectral reflectance spectra from soil samples have been used to model the total bitumen content in Canadian oil sands (*Lyder et al.*, 2010; *Rivard et al.*, 2010). However, in marine environments the oil type and the layer thickness are critical to the applicability of optical remote sensing for natural oil slick detection and identification (*Wettle et al.*, 2009).

The following main scientific tasks are related to the natural resource management:

- Develop algorithms and expert systems for *mineralogical mapping* with emphasis on alteration zones and index minerals of metamorphic zonations;
- Analyse the capability of hyperspectral data for the detection of *rare earth minerals* based on different globally distributed sites;
- Develop new algorithms and models for non-linear, weighted unmixing and mineral *quantification approaches;*
- Investigate the effects of mineral-induced stress on the spectral signature of dense vegetation canopies to establish a link between *vegetation stress* and specific minerals;
- Quantitatively estimate the influence of external (weathering crusts, lithobionts) and internal (organic matter, opaque accessory minerals) parameters on the spectral signature of rocks and soils – creation of *pedo-transfer functions*;
- Calibrate remote sensing-based *soil condition indices* against soil reference samples to better link spectral parameters with soil development models;
- Retrieve *soil properties*, such as organic matter and iron content, particle size distribution, clay mineralogy, water content, soil contamination, cation exchange capacity and calcium carbonate content to analyse status and changes of soils; and
- Develop methods to optimize *oil extraction* in order to improve ecosystem stability.

5.3.2 Environmental rehabilitation

The extraction of natural resources is frequently associated with environmental degradation due to the dispersion of potentially toxic substances. For example, numerous abandoned mines (e.g. open pit coal, copper and gold mines) have left an environmental legacy of acidic drainage and toxic metals in downstream watersheds, with adverse effects to human and ecosystem health (*Swayze et al.*, 2000). Acid mine drainage derives from an enhanced sulfide hydro-oxidation process due to the increased effective surface of crushed and milled rocks during the mining process. Sulfuric acid enters the food chain through contaminated soils and water, which can ultimately result in the collapse of wetlands (*McCarthy et al.*, 2007) and the decline of ecosystems (*Wepener et al.*, 2011). Imaging spectroscopy can effectively identify contaminations and determine its sources and downstream impacts on the water cycle and on vegetation health (*Clark et al.*, 2003). Hyperspectral mapping of areas affected by acid mine drainage has accelerated the site cleanup and saved millions of dollars in cleanup costs (*EPA*, 1998).

Based on an improved understanding of mining related environmental impacts many countries strengthened legislation to enforce environmental protection and to implement rehabilitation measures (*MMSD*, 2002). In this context imaging spectroscopy represents a comprehensive monitoring tool to assess the mining related environmental impacts and to monitor the progress of ecosystems restoration. In the event of oil spills, as happened in the Gulf of Mexico after the Deepwater Horizon explosion, imaging spectroscopy can accurately identify petroleum and discriminate it from terrestrial backgrounds (e.g. *Allen and Krekeler*, 2011). Therefore, EnMAP has the potential to become an efficient operational tool to monitor both the effects of environmental pollution and the progress made in the rehabilitation of affected sites.

The following main scientific tasks are related to environmental remediation:

- Develop geospatial tools and integration techniques for sustainable *mine site management*;
- Detect, quantify, and model the short- and long-term *environmental changes* caused by mining activities;
- Develop algorithms to automatically *detect mine waste* areas; and
- Assess and quantify the success of *remediation strategies.*

5.4 Hazards and Risks

With growing population and infrastructure the world's exposure to natural hazards is increasing (*Nellemann et al.*, 2008). In particular, coastal areas record the strongest increase in population growth concurrently with an increasing exposure to floods, cyclones and tidal waves. Natural hazards encompass a wide range of phenomena that range from geologic and climatic hazards to fires and diseases. These hazards occur on different timescales (e.g. earthquakes and droughts) and affect different spatial scales (e.g. landslides and geomagnetic storms).

Many natural occurring phenomena are growing to natural hazards once we are faced with their extremes. Thus, some topics described in this section are closely linked to other applications and research topics (e.g. algae blooms, soil contamination) and can also be synergistically adjusted to the needs of hazards and risks management. The specific demand for disaster management is described in the following section.

5.4.1 Disaster management

In case of a natural disaster the crisis management is described by the crisis cycle: starting with the (1) urgent crisis, followed by the phases of (2) emergency relief, (3) recovery, (4) reconstruction, (5) risk analysis, and (6) preparedness and alertness before closing the cycle with the next crisis. Most phases offer diverse opportunities for imaging spectroscopy to contribute to an improved and comprehensive crisis management.

In general, crisis information is needed at different stages before and after a disaster event with varying degrees of urgency. During the emergency relief phase crisis information is needed to minimize loss and damage. *Rapid mapping* based on hyperspectral data requires a high level of readily implemented and computationally efficient algorithms and procedures. Due to the high information content, given the large number of spectral bands, an operational use in the case of emergency has to be defined, tested and accurately described. The following main applications and tasks have been identified for different crisis phases, in which hyperspectral analysis can add significant information to existing sensors and analyses:

Emergency phase

- *detection of water or land pollution* (e.g. oil spill monitoring, detection of massive algae blooms, determination of chemical pollutant types during technical accidents, debris analysis in case of tsunamis, etc.)
- *detection of flood-affected areas along flood plains* (e.g. saturated soil and dams)
- *determination of different volcanic flows* in case of volcanic eruptions (lava of different ages, pyroclastic flows, and lahars) and deposits of other volcanic materials

Recovery phase

- *status of vegetation* (to estimate crop failure after hurricanes, hailstorms or during droughts)

Prevention phase

- *risk assessment* (e.g. prediction of oil spill spread direction and rate characteristics, assessment of contaminated areas, monitoring of vegetation status)

During previous disaster events airborne imaging spectroscopy data were employed to localize and identify materials related to oils spills, chemical pollutions, volcanic eruptions, and landslides. However, airborne imaging systems are of limited use to cover events of larger geographic extend on an operational level. In most previous disaster events imaging spectroscopy data were applied during the later reconstruction and risk analysis phase (monitoring of oil spills, identification and measuring of damage, assessment of the situation, scientific applications), rather than during the urgent emergency relief phase. Therefore, existing algorithms employed during later disaster management stages need to be automated and optimized to be operational during the pressing early disaster stages.

Such disaster applications require the following main scientific tasks:

- Development of new algorithms for *disaster mapping* using the hyperspectral band information;
- Development of time-efficient *image processing* techniques; and
- Monitor areas affected by natural hazards for *long-term studies* and to derive early warning indicators.

5.4.2 Natural hazards

Landslides

In mountainous areas landslides of various forms and compositions impose a constant threat to local communities and infrastructures. Landslide monitoring and hazard assessment studies have long been based on geomorphological analysis of remote sensing imagery (*Metternicht et al.*, 2005, and references therein). Traditional geomorphological landslide analysis can be improved with hyperspectral data to characterize active unstable slopes (debris-covered areas, fractured/disjointed rock walls, landslide accumulation borders) and individual structural features and landforms (major faults and fractures, trenches, elongated depressions, counterslope scarps) (*Mondino et al.*, 2009).

Floods

Many of the world's urban centres are subject to floods caused by rainstorms, snowmelt, or dam-failures. A major challenge related to flood monitoring is its timely detection given the sparse ground instrumentation and the broad regional extent of floods. To overcome this lack of data satellite imagery have been extensively used since the 1970s including advanced hyperspectral data. For example, *Ip et al.* (2006) developed change detection algorithms to identify and classify flood-induced changes, in hyperspectral images captured by Hyperion. This automatic ability to detect and monitor floods enables a more rapid respond to flood risks, assessment of damaged areas, and further studies of water quality changes (*Ip et al.*, 2006).

Droughts

Droughts can have a substantial impact on the ecosystem and agriculture of the affected area. For example, large-scale agricultural losses can have local to global socioeconomic implications in the form of income losses and increasing commodity prices (*Simelton et al.*, 2012; *Ubilava*, 2012). In general, drought periods lead to an increased fire susceptibility and tree mortality, whereas carbon uptake decreases significantly (*Nepstad et al.*, 1999; *Asner et al.*, 2000; *Williamson et al.*, 2000). In critical ecosystems, such as the Amazon forest, seasonal droughts may increase in severity through deforestation, more frequent El Niño Southern Oscillation episodes, and global warming (*Asner et al.*, 2004). Spaceborne imaging spectroscopy has large potential to study climate–vegetation interactions by detecting the state of vegetation on a regional scale (*Asner et al.*, 2004). Such ecosystem studies may yield in an increased accuracy of ecological models and could result in drought-preventive measures for agricultural areas.

Volcanoes

In concert with seismic and geodetic measurements, hyperspectral information on volcanic debris flows, pyroclastic materials, and gas emissions are fundamental to the understanding of eruptive systems (*Crowley et al.*, 2003; *Tralli et al.*, 2005). In particular, hyperspectral thermal information provides valuable insights into volcanic activity (*Cipar et al.*, 2010). While these studies illustrate the potential of a hyperspectral sensor in volcanic research, the approaches need to be fine-tuned and tailored to the information needs of crisis management. For example, the differentiation between various crater types, lava flow types and volcanic deposits would significantly improve the risk assessment to enable a timely planning of evacuation measures.

The following main scientific tasks are related to natural hazards:

- Monitor and identify tectonic and mineralogic characteristics of *active landslides* to improve hazard assessments;

- Detect and monitor *flood occurrences* to assess flood risks, damaged areas, and water quality changes;
- Detect the state of vegetation during *drought periods* to improve the accuracy of ecological models and to develop drought-preventive measures for agricultural areas; and
- Investigate *volcanic systems* with regard to their crater types, lava flow types and volcanic deposits to improve risk assessment and evacuation measures.

5.4.3 Man-made hazards

Land degradation

As a result of climatic variations and human mismanagement, deterioration in soil and plant cover has adversely affected nearly 70% of the world´s dry-lands that cover approximately one third of the continental surface of the Earth. These facts have led to the ratification, by almost 180 nations, of the UN Convention to Combat Desertification (*UNCCD*, 1994), which emphasizes the need to monitor and assess land degradation processes worldwide. Combating desertification requires an accurate knowledge of the current land degradation status and the magnitude of the potential hazard. It is widely agreed that accelerated erosion is one of the most important sources of land degradation that, together with the destruction of vegetation cover and structure, contributes to the potential increase of land degradation and desertification (*Pickup*, 1989).

EnMAP data holds considerable potential to assess various degrees of land degradation by retrieving important variables that control the susceptibility to soil erosion, such as soil compaction, surface roughness, infiltration rate, and soil moisture (*Haubrock et al.*, 2004, 2008). Due to distinct topsoil characteristics, soils previously affected by erosion can be spectrally distinguished from intact soils (*Dematte et al.*, 2000). Another manifestation of soil degradation is increased salinity, which is commonly caused by rising water tables induced by land clearing or irrigation. Here, imaging spectroscopy proved to be an effective tool to infer the degree of soil salinity as indicated by the shape of the hydroxyl absorption feature at 2200 nm and by the presence of indicator minerals such as gypsum or smectite (*Taylor et al.*, 2001; *Taylor*, 2004). Further applications to investigate land degradation based on hyperspectral imagery include the analysis of spatial patterns and temporal dynamics of desertification (*Asner and Heidebrecht*, 2005). Overall, EnMAP will open up new possibilities to assist agricultural land use and to combat land degradation.

Oil spills

Most prominently, imaging spectroscopy was employed to detect the occurrence and migration of oil spills. In marine environments hyperspectral data can be used to track an oil spill's areal extent, the oil thickness, and oil categories. For example, *Salem* (2001) developed methods to detect oil-polluted surfaces (soil and water) and to predict oil spill trajectories and migration rates for a quick disaster response. However, the spectral behaviour of oil in water is inherently a highly non-linear and variable phenomenon that changes depending on oil thickness and oil/water ratios (*Rand et al.*, 2011). In addition, hyperspectral imagery has been used to detect ecosystem changes by weathered oil in coastal littoral zones (*Bostater et al.*, 2011; *Salem*, 2005) and by oil-induced vegetation stress (*Li et al.*, 2005).

Marine litter

The pollution of marine and coastal environments with marine litter, which is mainly composed of plastics, has been identified as a long-term hazard for associated ecosystems (*Galgani et al.*, 2010; *UNEP*, 2009).

Continuously increasing disposal quantities and low plastic degrading rates (on the order of centuries) caused an increasing litter accumulation in these environments over the past decades. Marine litter causes several harms including entanglement of and ingestion by marine organisms (e.g., fishes, seabirds) (*Gregory*, 2009). Because persistent toxic substances, such as organochlorines (e.g., PCB, DDE, DDT) and others, are accumulating at high concentrations on the surface of plastics (e.g. *Mato et al.*, 2001; *Ogata et al.*, 2009), the ingestion of plastics by marine organisms represents the entrance point of those substances into the food chain (e.g. *Bjorndal et al.*, 1994; *Eriksson and Burton*, 2003; *Graham and Thompson*, 2009; *Boerger et al.*, 2010). However, whether there is enrichment or depletion within the food chain is subject to on-going research (*Zarfl et al.*, 2011). Despite a basic understanding of principle sources and sinks of plastic pollution, a detailed assessment of their quantities and transport pathways is still lacking (*Zarfl et al.*, 2011). Given that imaging spectroscopy is suitable to identify marine plastics (e.g. *Thompson et al.*, 2004; *Kuriyama et al.*, 2002), EnMAP might contribute to the localization of major pollution sources, sinks and pathways of marine litter. A potential application to localize marine litter is related to natural hazards like tsunamis and floods, which can act as transport agents for large amounts of artificial materials into the marine environment. A major challenge in such a scenario is the timely acquisition and analysis of remote sensing images, which requires the development of efficient image processing techniques for a near-real-time support to enable the removal of marine litter.

Industrial waste

Technical accidents or illegal dumpings that release toxic industrial waste typically contaminate the surrounding environment (*Mayes et al.*, 2011; *Minh et al.*, 2003; *Okoronkwo et al.*, 2006; *Wong et al.*, 2007). Against this background, imaging spectroscopy can be applied to quantify the distribution of toxic materials and to assess the degree of environmental contamination (*Kemper and Sommer*, 2004). Furthermore, hyperspectral applications on waste management provided information on the concentration and distribution of asbestos and other debris materials in the aftermath of the September 11$^{\text{th}}$ terrorist attacks (*Clark et al.*, 2001) and the assessment of mine waste contamination of mining dumps (*Mars and Crowley*, 2003).

The following main scientific tasks are related to man-made hazards:

- Monitor *land degradation processes* (erosion and deposition) by providing regular maps of soil status such as organic matter (TOC), $CaCO_3$, iron content, infiltration rate, salinity, and physical crusting development;
- Identify and quantify various *soil contaminants* through their specific spectral signatures or indicators (e.g., bio-indicators based on eco-toxicological effects on vegetation) linked to change in chemical composition of the polluted soil;
- Develop new algorithms and optimisation of existing modelling approaches for mapping coherent *indicators of the erosional state of soils*;
- Monitor vegetation distribution and characteristics in semi-arid and sub-humid ecosystems for land degradation purposes taking into account highly variable background substrates;
- Investigate *oil spills* with respect to their oil type, distribution, migration rates, and environmental impacts;
- Identify sources, sinks and pathways of *marine litter* during large-scale plastics discharge events (e.g. tsunamis); and
- Quantify the distribution of toxic materials in *waste dumping sites* and assess the degree of environmental contamination.

5.5 Atmospheric Research

Although EnMAP is not specifically designed for atmospheric research, variables that describe atmospheric conditions and constituents may be retrieved using EnMAP data. These variables include atmospheric water vapour, mineral dust, particulate matter clouds, and pollen.

Atmospheric water vapour is important for many environmental applications since it constitutes one of the most effective greenhouse gases in the atmosphere. It shows a high spatial and temporal variability depending on meteorological conditions and land use at the underlying Earth's surface. Information on the regional distribution of atmospheric water vapour may, for example, facilitate the analysis of SAR data since the radar signal transit time depends on the atmospheric conditions. A few algorithms for the retrieval of columnar water vapour content from hyperspectral remote sensing data have already been developed (e.g. *Barducci et al.*, 2004).

Atmospheric constituents such as mineral dust and particulate matter clouds originating from sand storm areas or biomass-burning activities also show a highly variable temporal and spatial distribution. Mineral composition of such transported dust is essential to our understanding of climate forcing, mineralogy of dust sources, aerosol optical properties, and mineral deposition to the ground. Furthermore, the differentiation of spectral signals from the ground and from mineral dust may allow separating atmospheric influences from the actual ground signal by determining their mineral composition. *Chudnovsky et al.* (2009) showed that, for the suspended dust, the absorption signature could be decoupled from scattering, allowing detection of key minerals. For vegetation and phenological studies temporal and spatial pattern of pollen spread may be retrieved from hyperspectral data as few studies have demonstrated (e.g. *Kaleita et al.*, 2006).

Accordingly, scientific tasks related to atmospheric applications include:

- Develop and improve algorithms to retrieve *columnar water vapour* based on hyperspectral data;
- Develop and improve algorithms to characterise *mineral dust, particulate matter clouds and pollen* based on hyperspectral data; and
- Develop and improve algorithms to *separate the spectral signal of mineral dust from the actual ground signal.*

6. Scientific exploitation strategy

To meet the overall objectives of the EnMAP mission a considerable amount of effort is dedicated to scientific exploitation activities with the aim to build and train a well-prepared community ready for an efficient and professional use of the EnMAP data, once they are available. This strategy is achieved by a bundle of activities that aim at spreading relevant information, increase public awareness and train the next generation of remote sensing scientists. This section provides a brief overview of the various activities related to the EnMAP mission.

6.1 Community information and public awareness

The primary source of information about the EnMAP mission is the official EnMAP website www.enmap.org. In addition, a mailing list was established to spread EnMAP-specific news and announcements. One can subscribe to the list by sending an email to EnMAP_wiss-on[at]gfz-potsdam.de. As of July 2012, the list has nearly 300 German and an increasing number of international subscribers from research, administration and business.

Research results related to EnMAP are frequently published in scientific journals and presented at international conferences. To raise the public awareness relevant information about the mission and its status are spread through the media (newspapers, TV, etc.).

Key documents of the EnMAP mission targeting the scientific community and other users are highlighted in Table 2. Note that some of these documents are under preparation and will be available at a later stage.

6.2 Community building and training

In the preparatory phase of the EnMAP mission various activities are in place to build and increase an expert scientific community in order to exploit the full information content of the EnMAP data.

National workshops are held in about 15 months intervals with the following objectives:

- to inform the scientific community on the progress of the mission
- to present and discuss the progress of the EnMAP-related research
- to form and enlarge the scientific community
- to raise awareness of the mission

In addition to the national workshops, EnMAP sessions at international conferences (e.g. EARSeL) are organized to present results and interact with the scientific community.

Table 2: Key documents of the EnMAP mission

Document	Authorship	Target group	Language	Objectives	Availability
Science Plan	PI and ECST	Scientists, funding institutions, environmental stakeholders and governmental bodies	eng	describe the scientific background, requirements, and activities related to the EnMAP mission	*www.enmap.org* (2012, continuously updated)
EnMAP flyer	Kayser-Threde and PI	General public	eng, ger	Brief information about mission, objectives and application fields	*www.enmap.org* (2012)
EnMAP brochure	PI and ECST	General public	eng, ger	Information about scientific objectives and application fields	*www.enmap.org* (2012, in preparation)
Hyper-spectral Algorithms report	PI and ECST	Hyperspectral community	eng	Overview of algorithms for hyperspectral analysis	*www.enmap.org* (2010)
Algorithm Theoretical Baseline Document (ATBD)	Ground segment	(potential) users of EnMAP data	eng	Detailed information on algorithms and databases used by the ground segment for data processing	*www.enmap.org* (final document due end of Phase D)
Mission Handbook	PI and ECST	(potential) users of EnMAP data	eng	Give mission overview, inform about AO-process, i.e. data access for science community	*www.enmap.org* (due 1 year ahead of launch, ½ year ahead of first AO)
Data User Handbook	Ground segment	(potential) users of EnMAP data	eng	Inform about data access (general and AO process), inform about main aspects of data policies (priorities, contingents), inform in detail about data (level, formats, processing, etc.)	*www.enmap.org* (due 1 year ahead of launch, ½ year ahead of first AO)

The *YoungEnMAP* group represents a research community of PhD students, early PostDocs and undergraduate students based at various universities and research institutes in Germany, which share ideas and experiences in the field of imaging spectroscopy. In order to promote and train these junior scientists, EnMAP summer schools are conducted by the ECST on an annual basis covering a broad range of themes. An additional communication and interaction tool represents the Internet platform "YoungEnMAP" (www.young-enmap.org), which is frequently used by the vibrant research group.

To facilitate convenient and straightforward processing and analysing of EnMAP data the EnMAP Box was developed. This Box represents a platform independent software interface, which is continuously advanced by the ECST and the EnMAP scientific community. For further information on documentation and installation of the EnMAP Box please refer to the EnMAP website (www.enmap.org).

6.3 Thematic and regional areas of interest

Flight campaigns

Hyperspectral data that derive from flight campaigns are crucial to simulate future EnMAP data. These data are required to develop and evaluate various methods and applications that can be readily employed during the mission operation period.

Appropriate study sites for such flight campaigns should be characterized by the following criteria:

- Cover at least one major research fields;
- Representativeness of the study area for these research fields;
- Long-term well-instrumented sites; and
- Pooling of interest groups if possible to reduce costs and use synergies.

Major study sites

During the EnMAP preparation programme period 2010 to 2012 the following study sites (sorted by research fields) were investigated by several flight campaigns (see Figure 6 for the approximate location).

- Agriculture: Neusling, Demmin, Köthen, Harz, Wahner Heide
- Forestry: Merzalben, Harz, Karlsruhe, Solling
- Land degradation: Oderbruch, Isabena (Spain), Castro Verde (Portugal)

Most of these sites are covered by multi-seasonal flights to support the analysis of multi-temporal process studies. Furthermore, acquisitions in different flight heights are obtained, which facilitate spatial scaling studies. In some occasions, the simultaneous data collection with other sensors (e.g., LiDAR) enables multi-sensoral studies. During each flight campaign extensive ground-data sampling is carried out to calibrate and validate the airborne acquisitions.

For the EnMAP preparation programme period 2013 to 2015 there are three to five flight campaigns planned per season at the main study sites Neusling, Demmin and Merzalben. Three additional sites are envisioned to augment this programme with approximately four flight campaigns per site to allow for multi-temporal analysis. The selection of these addition sites will be based on the above-mentioned criteria for study sites. In this concept, pre-processed data sets obtained during the previous period 2010 to 2012 form the basis for long-term analyses at each study site.

Background mission

In case of free acquisition capacities, images are collected according to a predefined background mission strategy. The background mission includes general areas of interest with respect to the scientific mission goals and the identified major test sites.

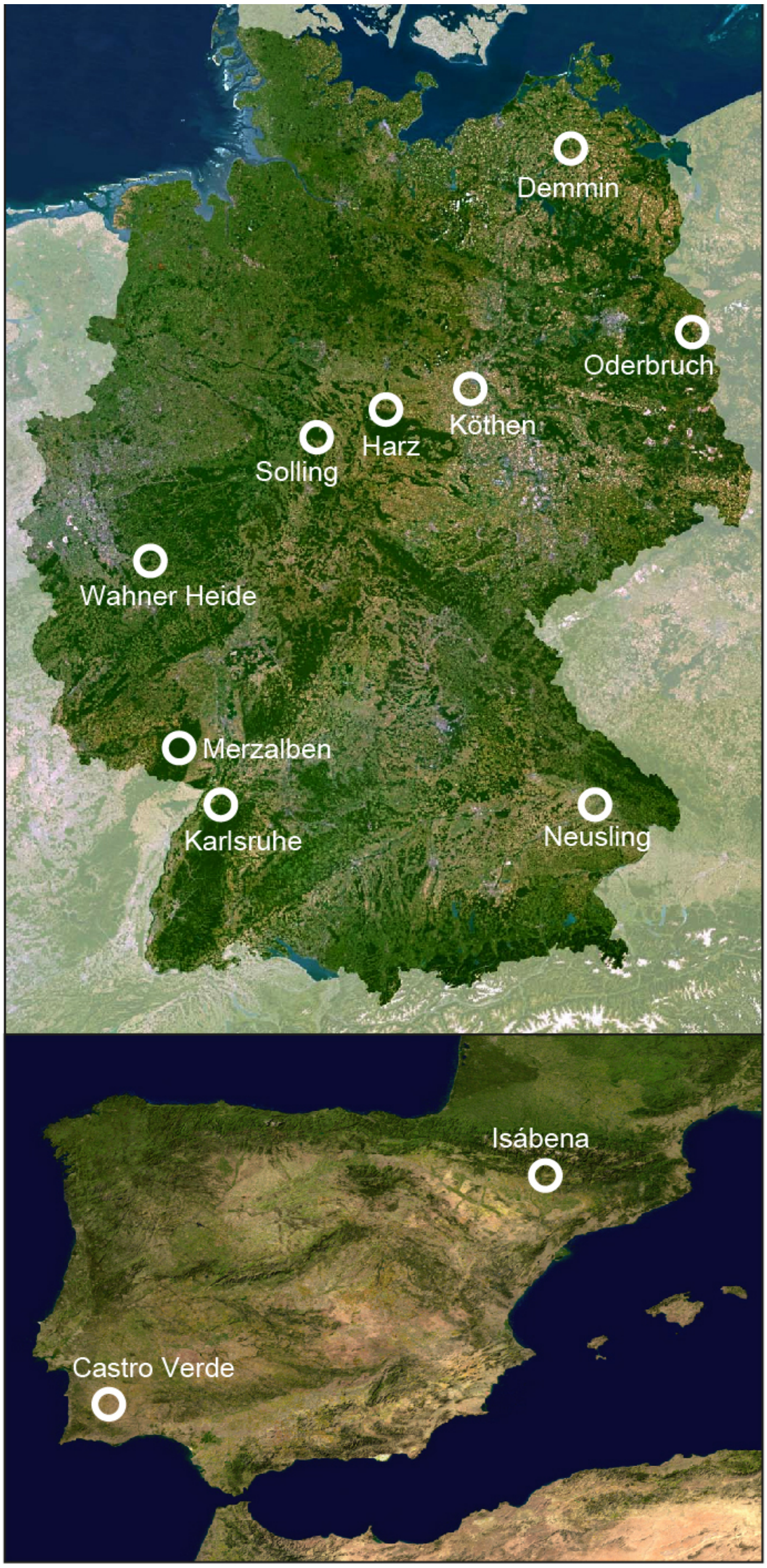

Figure 6: Location of study sites investigated with flight campaigns during the EnMAP preparation programme period 2010 to 2012

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Annex

Tables

Table A.1: List of organization, initiatives, and agreements relevant in the context of the EnMAP mission (as referred to in section 2.4).

Major Initiatives/Programs		
Abbreviation	**Name**	**Reference**
DIVERSITAS	International Program of Biodiversity Science	www.diversitas-international.org/
-	Future Earth	-
GBIF	Global Biodiversity Information Facility	www.gbif.org/
GCOS	Global Climate Observing System	gcos.wmo.int/
GEO	Global Environment Outlook	www.unep.org/geo/
GLP	Global Land Project	www.globallandproject.org/
GMES	Global Monitoring for Environment and Security	www.gmes.info
GOOS	Global Ocean Observing System	www.ioc-goos.org/
GTOS	Global Terrestrial Observing System	www.fao.org/gtos/
IGBP	International Geosphere-Biosphere Program	www.igbp.net/
LOICZ	Land Ocean Interaction in the Coastal Zone Program	www.loicz.org/
IHDP	International Human Dimensions Program	www.ihdp.unu.edu/
MA	Millennium Ecosystem Assessment	www.maweb.org/
REED+	Reducing Emissions from Deforestation and Forest Degradation including conservation and sustainable management of forests	www.un-redd.org
WCRP	World Climate Research Program	www.wcrp-climate.org/

International/European Organizations		
Abbreviation	**Name**	**Reference**
EEA	European Environmental Agency	www.eea.europa.eu/
-	EUROSTAT	epp.eurostat.ec.europa.eu
FAO	United Nations Food and Agriculture Organization	www.fao.org/
IOC	Intergovernmental Oceanographic Commission	ioc-unesco.org/
ICSU	International Council for Science	www.icsu.org/
IPBES	Intergovernmental Platform on Biodiversity & Ecosystem Services	www.ipbes.net/
IPCC	Intergovernmental Panel on Climate Change	www.ipcc.ch/
IUCN	International Union for Conservation of Nature	www.iucn.org/
UNEP	United Nations Environment Programme	www.unep.org/
UNESCO	United Nations Educational, Scientific, and Cultural Organization	www.unesco.org/
WMO	World Meteorological Organization	www.wmo.int/

Multilateral Agreements		
Abbreviation	**Name**	**Reference**
-	Aarhus Convention	ec.europa.eu/environment/aarhus/
-	Barcelona Convention	www.unep.ch/regionalseas/regions/med/t_barcel.htm
CBD	United Nations Framework Convention on Biological Diversity	www.cbd.int/
-	EU Water Framework Directive	ec.europa.eu/environment/water/water-framework/
-	Mediterranean Action Plan	www.unep.ch/regionalseas/regions/med/medint.htm
UNCCD	United Nations Framework Convention to Combat Desertification	www.unccd.int/
UNFCCC	United Nations Framework Convention on Climate Change	unfccc.int/

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