

## A REVIEW OF *IN-SITU* SAMPLING PROTOCOLS TO SUPPORT THE REMOTE SENSING OF VEGETATION

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## ABSTRACT

In spite of the recognized relevance of *in-situ* data to properly calibrate and/or validate remote sensing derived products, issues related to field data acquisitions are generally overlooked and poorly addressed. There are only a few specific references available in the literature that propose or describe field protocols for *in-situ* plant trait observations related to remote sensing studies. As such, this article aims to review the most relevant protocols available in the literature, including those developed through international initiatives, which discuss *in-situ* sampling considerations of plant traits for the remote sensing of vegetation and ecosystems. A survey was designed to gain an understanding of the main field acquisition protocols and practices currently being applied in various European institutions participating in the Marie-Skłodowska Curie Innovative Training Network (ITN) named 'Training on Remote Sensing for Ecosystem ModElling' (TRuStEE). We also discuss general considerations for experimental designs of field sampling, including spatial/scaling issues from the field to pixel level, seasonal and phenological characterizations, data management and ecosystem specificities. The overall aim is to provide an integrated assessment of the general issues and good practices that need to be considered to design an adequate field campaign protocol to support the remote sensing of vegetation.

Keywords: remote sensing; plant traits; field data; protocols; datasets



## REVISIÓN DE PROTOCOLOS DEL MUESTREO *IN-SITU* PARA APOYAR ESTUDIOS DE VEGETACIÓN CON TELEDETECCIÓN

#### RESUMEN

A pesar de la reconocida importancia de los datos in situ para calibrar y/o validar adecuadamente los productos de teledetección, las cuestiones relacionadas con la adquisición de datos sobre el terreno suelen abordarse de forma deficiente. Sólo unas pocas referencias específicas disponibles en la literatura proponen o describen protocolos de campo para las observaciones de rasgos funcionales de la vegetación in situ relacionadas con los estudios de teledetección. Por ello, este artículo revisa los protocolos más relevantes disponibles en la literatura, incluyendo los desarrollados a través de iniciativas internacionales, que discuten consideraciones relacionadas con el muestreo in situ de rasgos funcionales para el seguimiento de los ecosistemas con teledetección. Se diseñó una encuesta para conocer los principales protocolos y prácticas de adquisición de datos sobre el terreno que aplican grupos de investigación pertenecientes a diversas instituciones europeas y participantes en la red de formación Marie-Skłodowska Curie (ITN) denominada "Training on Remote Sensing for Ecosystem ModElling" (TRuStEE). También se discuten consideraciones generales en relación a los diseños experimentales para la adquisición de datos de campo, incluyendo las cuestiones espaciales y de escala (desde el dato de campo hasta el nivel de píxel), las caracterizaciones estacionales y fenológicas, la gestión de datos y las especificidades propias de diferentes ecosistemas. El objetivo general es proporcionar una evaluación integrada de las cuestiones generales y las buenas prácticas que deben tenerse en cuenta para diseñar un protocolo adecuado para la planificación de campañas de campo que sirvan de apoyo a la teledetección de la vegetación.

Palabras clave: teledetección; rasgos funcionales; datos de campo; protocolos; base de datos

#### 1. Introduction

Vegetative systems, through biotic and abiotic exchange mechanisms, have a large influence on global biogeochemical cycles and ecological functioning. Plant traits, morphological, biochemical and phenological features (Kattge *et al.*, 2011), quantify how vegetation respond to environmental factors and processes, being critical inputs for Earth system models. As such, plant trait monitoring has important implications to assess ecosystem functioning and services, to understand global energy, carbon and nutrient cycling, and to improve water and agricultural management. As a result, there is a growing consensus within the ecological research communities of the need to standardize the definition and measurement of plant traits (Fernández *et al.*, 2020; Homolová *et al.*, 2013; Kissling *et al.*, 2018).

The field of remote sensing (RS) has grown considerably over the years and has begun to gain traction as a viable scientific approach to address global biogeochemical (*e.g.*, Jung *et al.*, 2011, 2020), biodiversity (Kissling *et al.*, 2018; Skidmore *et al.*, 2021) and ecological (Houborg *et al.*, 2015; Ustin & Middleton, 2021) challenges. RS methods estimate plants traits by analyzing canopy/leaf light interactions (*i.e.*, spectral traits) and their characterization within the electromagnetic spectrum (Homolová *et al.*, 2013; Van Cleemput *et al.*, 2021). This has traditionally been based on spectral properties in the shortwave spectral regions (*i.e.*, visible to shortwave infrared, 0.3-3  $\mu$ m). However, thermal infrared (TIR, 3-14  $\mu$ m) regions can also describe valuable plant components, including

chemical and temperature characteristics of vegetation (Neinavaz *et al.*, 2021). TIR remote sensing, along with the use of surface energy balance models, is also crucial for global water and heat flux estimations (Kustas & Anderson, 2009), which are highly related to ecosystem functioning and plant traits. The improvement in spatial, spectral and temporal resolution of RS sensors has greatly improved the retrievals of many plant traits and ecosystem functional properties (Homolová *et al.*, 2013; Ustin & Middleton, 2021). The greatest advantage provided by RS methods is the consideration of processes within a spatial and temporal dimension, depending on the revisit time and pixel resolution, from plot to global and daily to seasonal scales.

Most RS techniques require extensive ground or *in-situ* data to parameterize, calibrate and/or validate the empirically or physically based methods applied. However, standard field protocols to sample the plant traits of vegetation for remote sensing studies are still largely lacking. While certain references have proposed some standardization procedures (e.g., Jiménez & Díaz-Delgado, 2015; Kissling et al., 2018; McCoy, 2005; Op de Beeck et al., 2017a), these are often adjusted for specific parameters, ecosystem types and disciplines. The fact that different research groups/projects have a variety of objectives, research lines, study scales and/or budget has led to a lack of standardization, which impede data sharing and inter-comparison (Schweiger, 2020). The research objective and the level of detail required (e.g., the spatial and temporal variability of the target) will determine sampling design and protocols. A lack of standard, or at least "good" practices/reference handbook, limits the comparability and transferability of *in-situ* plant trait data between studies, since ground information is subjected to local environmental conditions and sampling techniques (Rüegg et al., 2014). This induces that, despite the great efforts used to acquire field measurements, these are often only applicable to a single point and time because not enough samples were taken, metadata were not recorded, data was not well formatted and/or the collection method was not adequately described (Pfitzner et al., 2011). On top of this, in ecosystem modeling, there is often a mismatch in the terminology used between RS and ecology that also affect data comparability (Van Cleemput et al., 2021).

The overarching aim of this work is to provide a review on the currently available *in-situ* plant trait acquisition protocols and datasets and discuss field experimental design issues that are relevant to link field observations with RS methods. To obtain a preliminary overview of the current field data acquisition practices across different institutions, a survey was established and passed among research groups participating in the European Union Marie-Skłodowska Curie Innovative Training Network (ITN) named *'Training on Remote Sensing for Ecosystem ModElling'* (TRuStEE, <u>https://cordis.europa.eu/project/id/721995</u>). The survey results provided an understanding of current practices and needs of field data acquisitions in leading research groups across Europe with specific and complementary expertise on ecosystem modelling, plant physiology and remote sensing. We also demonstrate, on the basis of experiments implementing statistical analyses, the optimal field campaign design to adequately represent the ecosystem's spatio-temporal variability and to better support RS methods.

# 2. Are *in-situ* plant trait acquisition issues relevant to the remote sensing of vegetation community?

In order to better understand how field data acquisition is considered or not an issue among the RS community, a small survey was given in 2018 to TRuStEE ITN research groups integrated by



plant ecophysiologists, ecosystem ecologists, data-mining experts and ecosystem modellers with strategic focus on RS of ecosystem functioning. The survey aimed to characterize the different plant traits sampled throughout the network and to observe which types of protocols were being used. The sample pool consisted of responses from 10 research groups from various institutions across the TRuStEE network including: Fondazione Edmund Mach (Italy), University of Twente (Netherlands), Max Planck institute of Biogeochemistry (Germany), University of Milano-Bicocca (Italy), VITO (Belgium), Aerovision (Netherlands) and the Spanish National Research Council (Spain). Fig. 1 shows the main study sites and land cover types used by the survey respondents. The experimental sites were classified as savannas (40 %), croplands (20 %), grasslands (20 %), fruit orchards (10 %) and mixed/heterogenous (10 %) ecosystems. Fig. 2 depicts the main plant traits sampled by the different respondents and Table 1 lists the variable acronyms and definitions.



Figure 1. Location of experimental sites of survey respondents and the respective land cover type.



**Figure 2. The number of respondents that sampled each** plant trait along with their acquisition frequency (*i.e.*, 'occasionally' in yellow, 'frequently' in green and 'always' in red) during typical field campaigns.



Plant Traits	Description	Units	Applications		
LAI	Leaf Area Index. Total one- sided area of photosynthetic tissue per ground surface area	m <sup>2</sup> /m <sup>2</sup>	Often used to upscale properties from the leaf to canopy scale. LAI characterizes phenological growth, plant structure and response to stress, providing also critical information to understand the carbon, water and, ultimately, the energy budget.		
LAD	Leaf inclination angle distribution. Orientation of leaves in canopy	Degrees	Influences light interception and how it interacts among leaf layers. Key input/parameter for radiative transfer models.		
PWC	Plant Water Content. Measure of leaf or canopy water content as mass or concentration.	kg/m <sup>2</sup> or %	Important for biogeochemical cycling, drought monitoring, water stress indicator, irrigation practices.		
AGB	Above ground biomass of vegetation	kg/m <sup>2</sup>	Related with land-atmospheric gas, matter and energy exchanges. Relevant to analyze carbon sink and agricultural productivity.		
Cab	Chlorophyl a+b. Green plant pigments that absorb solar radiation for photosynthesis	mg/m <sup>2</sup> or mg/g	Vital for the photosynthetic process and, thus, plant growth, carbon cycling, matter and energy exchanges. It is used as a biomarker for an acute environmental stress, as an indicator of vegetation gross primary productivity. Key input parameter for radiative transfer and physiological ecosystem models.		
Car	Carotenoids.	mg/m <sup>2</sup> or mg/g	Absorb light for photosynthesis and protect chlorophyll from photodamage. The ratio of Car and Cab is and indicator of foliar senescence.		
Ν	Nitrogen.	mg/m <sup>2</sup>	Important role in the production of chlorophyll. Often		
		or mg/g	limiting factor for plant/crop growth.		
SIF	Sun-Induced Fluorescence. The re-emission of excess light energy by plants.	mmol $m^{-2} s^{-1}$	Important information on the photosynthetic capacity and physiological status of vegetation.		
SLA	Specific Leaf Area. The ratio of leaf area to dry mass.	cm <sup>2</sup> /g	Indicator of reproductive strategy of plant species. Indicates investment in durable leaf tissues.		

Table 1. Selected Plant Traits typically sampled during field campaigns related to the remote sensing of vegetation

Leaf area index (LAI), Chlorophyll a+b (Cab) and specific leaf area (SLA) were the most sampled plant traits by the TRuStEE community, where 80 %, 70 %, and 70 % of respondents at least occasionally sample the respective trait. Leaf angle distribution (LAD) was the least sampled parameter with only 20 % respondents occasionally sampling this parameter. This likely reflects the complexity in acquiring LAD using field measurements even though it is notably important in radiative transfer modeling (Verrelst *et al.*, 2015). Most respondents acquired field data to parameterize physically-based models (80 %) (Fig. 3) and to estimate biophysical/plant traits (80 %)



and/or biogeochemical fluxes (60 %). The sharing of field data within and/or between groups is customary practice where 90 % respondents claim to do so, including 60 % of respondents sharing data with researchers worldwide (Fig. 4). Indeed, 38 % of respondents use self-designed protocols, while 45 % rely on sources from the literature or specialized websites (Fig. 5). This is an indication of the importance of standardized methodologies and data organization to make field data compatible between different groups, and to maximize reliability and shareability.



Figure 3. Survey results on the purposes and uses of field data acquisition for their remote sensing applications



Figure 4. Survey results on whether the respondents share the data collected from their experimental sites





Figure 5. Survey results from respondents defining which type of source(s) were used to design protocols for plant trait sampling.

#### 2. International initiatives to standardize field protocols and databases

#### 2.1 Standardized protocols of in-situ plant trait observations

Many international initiatives have aimed to standardize field data acquisitions of plant traits for ecological, biogeochemical and/or ecosystem modeling applications. Often, these protocols focus on specific ecosystems (*e.g.*, grasslands) or for a specific type of application (*e.g.*, biodiversity conservation) not necessarily accounting for RS needs.

The Integrated Carbon Observation System (ICOS) Ecosystem Thematic Centre developed several technical protocols related to the setup, management and measurement of biophysical and atmospheric variables. These are mainly concentrated on supporting field experimental stations related to the monitoring and understanding of carbon and other greenhouse gas exchanges. Detailed field protocols (<u>http://www.icos-etc.eu/icos/documents/instructions</u>) are available for various types of data acquisitions including eddy covariance (EC) systems for energy and turbulent fluxes, meteorology and vegetation traits. Field measurements of biophysical parameters are adapted for different ecosystem types including cropland (Gielen *et al.*, 2017a), forest (Gielen *et al.*, 2017b), grassland (Op de Beeck *et al.*, 2017a) and mire/peatland systems (Op de Beeck *et al.*, 2017b). These protocols include an extensive review of the main measurement methods to retrieve green area index (GAI), above-ground biomass (AGB) and litter for the different ecosystem classes. Along with this, recommendations are provided for sampling design and data organization, including spatial and temporal considerations, for both destructive and non-destructive methods.

Cornelissen *et al.* (2003) presented a handbook for standardized measurements of plant functional traits. This handbook was developed by a group of international scientists through a workshop organized by the International Geosphere-Biosphere Programme (IGBP). One of the objectives of this workshop was to initiate simple trait measuring protocols for worldwide use (Cornelissen *et al.*, 2003). The handbook provided recommendations on plant/sample selection, including statistical considerations for sampling activities to represent the community or ecosystem in question, along with specific methodologies for field trait measurements. The variables described in the handbook were organized under vegetative traits, leaf traits, stem traits, below-ground traits and regenerative traits. This handbook was further updated and expanded in Perez-Harguindeguy *et al.* (2013). Futhermore, Klimešová *et al.* (2019) also presented a handbook for standardized field



measurements of 14 plant functional traits that were grouped into five groups: Anatomical features, Bud bank, Carbohydrate storage, Clonality and Longevity and growth. However, these handbooks were designed within an ecological framework rather than for RS applications.

The Group of Earth Observations Biodiversity Observation Network (GEO BON, Pereira *et al.*, 2013) introduced the concept of Essential Biodiversity Variables (EBVs) to harmonize and standardize biodiversity data globally from disparate sources (Pereira *et al.*, 2013). Fernández *et al.*, (2020) framed an overview on how to integrate *in-situ* observations with remote sensing modeling to monitor EBVs while Kissling *et al.* (2018) suggested 11 steps to build *'spatially continuous and temporally consistent EBV products'*, which integrate traditional *in-situ* observations with remote sensing data. Rüegg *et al.* (2014) emphasized the importance of integrated information management during ecological data collection. This was related to the need for more documented and transparent datasets that can easily be shared and re-used across different researchers and stakeholders (Hugo *et al.*, 2017; Rüegg *et al.*, 2014).

The National Science Foundation's National Ecological Observatory Network (NEON) is a continental-scale observation network with 81 field sites across the USA (https://www.neonscience.org/). This network collects field-based bio-physical-chemical measurements of vegetation and water, along with continuous atmospheric measurements and periodic airborne remote sensing acquisitions. All NEON measurement protocols are freely available, which include ground measurements of canopy foliage (e.g., total organic carbon, nitrogen, chlorophyll), leaf area index (LAI), vegetation structure and above/below ground biomass. These combine different direct and indirect measurement techniques and are consistent across all field sites. They also provide protocols and guidelines on data management and processing practices. A key advantage of NEON is the integration of field data along with remote sensing data, allowing for a full and integrated assimilation of both datasets

The Global Airborne Observatory (GAO) utilizes Earth Observation imagery techniques to support environmental conservation efforts (Asner & Martin, 2016). The GAO has published, within their website, technical protocols for field and laboratory procedures (https://gao.asu.edu/spectranomics). These include procedures for *in-situ* leaf collection, processing, transportation, and spectroscopy measurements. Along with this, details are available for laboratory procedures to extract various plants traits including water content, specific leaf area, carbon, nitrogen, and chlorophyll-carotenoids (among others).

The Global Terrestrial Observation System (GTOS) from the Food and Agriculture Organization of the United Nations (FAO) created a manual for biological measurements of biomass, primary production and other ecosystem processes in forest ecosystems (Law *et al.*, 2008). It was developed for North American forests; however, the authors indicated that it may serve as a guideline to obtain consistent data at the global level. Detailed sampling design and field methodology were elaborated for different vegetation and soil parameters related to terrestrial carbon cycle science (Law *et al.*, 2008).

The book 'Field methods in Remote Sensing' (McCoy, 2005) provided an extensive overview of the variety of issues to consider when field sampling for remote sensing methods. The purpose was to introduce the fundamentals of fieldwork related to remote sensing, including project planning, selecting appropriate spectral training sites, and basic measurements methods for vegetation, soil and

water (McCoy, 2005). This is a good reference for general recommendations for designing an experiment or protocol for field campaigns. However, it elaborates very briefly on specific procedures for the *in-situ* acquisition of vegetative plant traits. Similarly, the USGS/NPS vegetation mapping program published a field protocol (USGS/NPS Vegetation Mapping Program, 1994) to standardize land use and vegetation mapping. The document discusses field theory, sampling design, data management and how to evaluate information on biology, ecology and land use history for vegetative mapping protocol (USGS/NPS Vegetation Mapping Program, 1994).

The Soil Moisture Experiments (SMEX) were large scale field campaigns that occurred between 2002-2005 (SMEX02, SMEX03, SMEX04 and SMEX05) with the aim to better understand landatmospheric interactions by validating brightness temperature and soil moisture estimations from satellite observation systems and to extend algorithms and instrumentation for their retrievals (Jackson *et al.*, 2008). Intensive field campaigns were performed in Arizona to obtain ground measurements of soil moisture, surface temperature/reflectance and vegetation traits (plant height, LAI, dry and green biomass). Details on sampling design and protocols are available from their experiment plan (https://www.eol.ucar.edu/system/files/SMEX04v1.pdf).

The National Fuel Moisture Database (NFMD) in the USA has a country-wide dataset on dead and live fuel moisture. They also provide a sampling guideline for these parameters created by the Bureau of Land Management from the Utah State Office (Pollet & Brown, 2007). Another Fuel Moisture Content (FMC) protocol was detailed in Chuvieco *et al.* (2003). This reference demonstrated a field and laboratory protocol to calculate field FMC for shrubs and herbaceous plants in Mediterranean ecosystems. The Globe-LFMC dataset (Yebra *et al.*, 2019) designed a framework on how to merge data from different organizations and protocols into a global live FMC dataset. Joly (1985) discussed a review on field/laboratory methodology to assess plant water status as an indicator for stress. This review outlined measurement methods for relative water content, total plant water potential and osmotic potential. Garnier *et al.* (2001) detailed a standard protocol for leaf dry matter content (LDMC) and specific leaf area (SLA), including testing the length of the rehydration period needed to obtain the weight of samples at full turgor. They proposed a method for leaf sampling selection, sample treatment and transportation and laboratory protocols.

Several protocols are also available related to field spectroscopy and proximal sensing (*e.g.*, Held *et al.*, 2015; Pfitzner *et al.*, 2011; Rasaiah *et al.*, 2014; Schweiger, 2020). While not directly informing on plant trait acquisitions, similar concepts and good practices, for example sampling scales and metadata collection, may be transposed to *in-situ* plant trait acquisitions. For instance, Australia's Terrestrial Ecosystem Research Network (TERN, Held *et al.*, 2015), provided comprehensive protocols and guidelines for field spectroscopy and good practices for field data collection supporting Earth Observation research, including field data management and lifecycle, and recommending sampling designs (Held *et al.*, 2015). In fact, the Chapter 6 and 12 of Held *et al.* (2015) also review both destructive and non-destructive ground-based measurement techniques for LAI and AGB, respectively. Milton *et al.* (2009) reviewed the main progresses and history of field spectroscopy over the years, including discussing practical aspects of *in-situ* measurements. Pfitzner *et al.* (2011) coordinated a scientific report by the Supervising Scientific Division (SSD) of the Department of Sustainability, Environment, Water, Populations and Communities (SEWPaC) within the Australian government. This report presents a robust methodology for collecting field reflectance spectra of vegetative ground cover with the aim to minimize errors from external factors and establishing links

between spectra and metadata (Pfitzner *et al.*, 2011). This document discussed issues with acquiring *in situ* spectral data, factors influencing measurements, appropriate metadata and detailed a specific field spectroscopy protocol. Rasaiah *et al.* (2014) outlined a standardization of field spectroscopy metadata based on an international experiment that used a web-based survey and a panel of experts to investigate the most critical metadata needed for field spectroscopy.

## 2.2 Plant trait datasets

As this review suggests, field measurements of plant traits would highly benefit from standardization procedures. Congruent to this, the availability of global databases of plant traits would also improve and facilitate the sharing and the broader usefulness of the acquired field data.

GLOPNET, Global Plant Trait network, combined data from various research groups and biomes to the compilation and sharing of leaf encourage trait data (http://bio.mq.edu.au/~iwright/glopian.htm). The project is led by Peter Reich (U.Minesota), David Ackerly (UC Berkeley), Ian Wright (Macquarie University) and Mark Westoby (Macquarie University) and have compiled data for 175 sites worldwide, representing every biome, and acquiring data such as specific leaf area, leaf thickness, leaf lifespan, photosynthetic capacity and nutrient concentrations.

The LEDA Traitbase is a plant life history database for Northwest European flora to describe plant persistence, regeneration, and dispersal (<u>https://www.uni-oldenburg.de/en/landeco/research/leda/</u>). The database includes traits such as canopy height, leaf dry matter content, leaf size, plant life span, seed mass and specific leaf area. The project is led by the Landscape Ecology Group of the Carl von Ossietzky University of Oldenburg (Germany) with funding from the European Union 5<sup>th</sup> Framework Programme for Research within Energy, Environment and Sustainable Development Programme. The database is also supported and maintained by the German Federal Agency for Nature Conservation.

One of the most comprehensive and global datasets dedicated to plant traits is the TRY dataset (Kattge *et al.*, 2011) developed by Future Earth (<u>https://futureearth.org/</u>) and the Max Planck Institute for Biogeochemistry (TRY data portal: <u>https://www.try-db.org/TryWeb/Home.php</u>). The database begun in 2007 and has grown substantially to a nearly global coverage of more than 15000 measurement field sites with records of 2100 traits (version 5 released in March 2019). The TRY initiative has integrated more than 400 datasets including from collective databases such as LEDA, GlopNet and others. The main purpose of this dataset is to provide an online-based archive of functional biodiversity of plants at the global scale by assembling, harmonizing and distributing functional plant traits along with their metadata.

The BROT database (<u>https://www.uv.es/jgpausas/brot.htm</u>) was developed to organize firerelated plant traits of Mediterranean basin species. Traits related to plant persistence and regeneration after fire are documented including average height, average leaf size, resprouting ability, shoot:root ratio and leaf phenology. This database was developed under the projects of EUFireLab (<u>http://www.eufirelab.org/</u>), PERSIST (<u>https://www.uv.es/jgpausas/persist.htm</u>) and CIRCE. In



addition, the Globe-LFMC database (<u>https://www.nature.com/articles/s41597-019-0164-9</u>) provides a global Live Fuel Moisture Content product with measurements from 1,383 sampling sites from 11 countries (Yebra *et al.*, 2019).

NEON also freely shares the data collected throughout its 81 sites in USA (<u>https://data.neonscience.org/data-products/explore</u>). These include measurements at multiple scales including the collected *in-situ* plant traits related to vegetation structure and biomass along with continuous flux and meteorological measurements. They also provide remote sensing airborne acquisitions taken over the peak biomass period over their field sites. These airborne overpasses are equipped with a hyperspectral spectrometer, a Lidar sensor and an RGB camera (<u>https://www.neonscience.org/data-collection/airborne-remote-sensing</u>).

Other datasets are generally linked to projects, geographical areas and/or specific plant trait parameters. For instance, the Soil Moisture Experiment (SMEX) campaigns (SMEX02, 03, 04 and 05) have published data (https://nsidc.org/data/amsr validation/soil moisture/index.html) acquired from their intensive field campaigns between 2002 and 2005. Data include soil moisture, vegetation (LAI, CWC, and proximal reflectance), meteorological, land classification, airborne remote sensing data and satellite remote sensing data for field sites in the United States (Iowa, Alabama, Georgia, Oklahoma, Arizona) and Mexico (Sonora). There are also country specific databases such as database of ecological traits of New Zealand (here: https://ecotraits.landcareresearch.co.nz/) and USDA Plants (https://plants.sc.egov.usda.gov/java/), which provide standardized information about vascular plants, mosses, liverworts, hornworts and lichens in the United States. The United States also have a national fuel moisture database (NFMD) that provides a system to obtain live and dead vegetation fuel moisture information. The database is routinely updated with specialists who sample and monitor fuel moisture content across the United States. The BIOSPEC (http://www.lineas.cchs.csic.es/biospec/), FLUXPEC (http://www.lineas.cchs.csic.es/fluxpec/structure) and **SynerTGE** (http://www.lineas.cchs.csic.es/synertge/project overview) projects have also developed a relatively continuous database (since 2009) of herbaceous and tree traits (e.g., biomass, water content, LAI, chlorophyll) for a Mediterranean agro-forestry ecosystem in western Spain. Biophysical measurements are taken along with *in-situ* spectro-radiometric measurements to apply RS methods at multiple scales (Burchard-Levine et al., 2021; Melendo-Vega et al., 2017; Mendiguren et al., 2015). These projects were led by the Environmental Remote Sensing and Spectroscopy Laboratory (SpecLab) at the Spanish National Research Council (CSIC) and the data are available upon request.

#### 3. General Sampling considerations in the elaboration of field protocols

Field protocols must incorporate a field sampling design that is pertinent to the unique features of the study in question. The following sections aim to elaborate on some of the practical issues that should be considered when performing a field campaign supporting Earth Observation methods. The intention is not to provide an explicit protocol for each parameter and ecosystem type, since protocols always need to be adapted to the unique considerations of the study, including adjusting for parameter type, ecosystem characteristics and research objectives. Rather, general issues



and considerations were discussed such as sampling size, capturing spatial and temporal variability, ecosystem specificities and data organization.

#### 3.1 Sampling size

In statistical terms, a sample is a subset of a population. In other words, the acquired sample should represent the entire space of interest. Therefore, the optimal sample size needed is a common predicament when designing a field protocol. There needs to be a balance between factors such as time, personnel and economic resources and the amount of data needed to scientifically represent the methods that will be used to further process the information (Held *et al.*, 2015).

We exemplify relevant issues related with sampling size selection using a field experiment performed in the context of BIOSPEC (<u>http://www.lineas.cchs.csic.es/biospec/</u>) and FLUXPEC (<u>http://www.lineas.cchs.csic.es/fluxpec/project\_overview</u>) projects. The experiment was designed to investigate how sample size affects the accuracy of equivalent water thickness (EWT) measurements in semi-arid grasslands. Three 25 m x 25 m plots were selected and, within each plot, two samples were taken from 25 cm x 25 cm quadrants. Each quadrant sample was further subdivided into nine sub-samples (Fig. 6). The experiment was conducted to estimate the error associated with EWT measurements from sub-samples as opposed to using the entire sample in a highly diverse grassland ecosystem.



Figure 6. Schematic representation of the experiment that tested the errors of harvested grass equivalent water thickness (EWT) associated with the sample size of a 25 cm x 25 cm quadrant subdivided into nine sub-samples. Two 25 cm x 25 cm quadrants were harvested for each 25 m x 25 m plot.



In total, 54 grass sub-samples were acquired (3 plots  $\times$  2 samples  $\times$  9 subsamples). The relative root mean square error (RRMSE) was computed for each sample using the whole sample (*i.e.*, 9/9 subsamples) as the 'observed' value (Fig. 7).



Figure 7. RRMSE estimated by comparing equivalent water thickness (EWT) measurements from subsamples vs the whole quadrant sample (9/9 subsamples)

As shown in Fig. 7, sampling only  $1/9^{\text{th}}$  of the quadrant will generate an error between 7 % and 26 % for the estimation of EWT, while sampling roughly half of the whole quadrant is associated with a maximum RRMSE of about 12 %.

Using the same experimental design, all possible combinations of sub-samples were tested to observe the effect of sample size on the overall mean result between the six EWT samples (3 plots, 2 samples each). All cases for possible sub-sample combinations were taken into account, except when the number of cases exceeded  $10^8$ . In this situation,  $10^8$  cases were randomly selected. The random selection process was repeated numerous times and the resulting RRMSE variation is negligible (< $10^{-6}$ ) even when the percentage of selection was very low compared to the total number of cases. Table 2 highlights the results of this analysis and demonstrated that the sample size can be reduced to 6/9 of the total sample and still ensure an error of EWT less than 3 % for the overall measurements acquired during the sampling date.



Sub-sample size	Number of cases per plot	Number of samples	Total Number of cases	Number of cases selected	Proportion of cases selected (%)	RRMSE (%)
s 1/9	9	6	5.31E+05	531441	100	11.90
s 2/9	36	6	2.18E+09	100000000	4.59	7.87
s 3/9	84	6	3.51E+11	100000000	0.028	5.95
s 4/9	126	6	4.00E+12	100000000	0.0025	4.71
s 5/9	126	6	4.00E+12	100000000	0.0025	3.76
s 6/9	84	6	3.51E+11	100000000	0.028	2.98
s 7/9	36	6	2.18E+09	100000000	4.59	2.25
s 8/9	9	6	5.31E+05	531441	100	1.49
s 9/9	1	6	1.00E+00	1	100	0

|--|

There is not a single solution to implement the optimal sample size within an experimental design as it mostly depends on the site conditions and research questions. However, analyses similar to this are recommended to guarantee an adequate decision and design that represents the plot conditions. The sampling protocol must also balance between the time/resources needed to perform the measurements, the maximum error associated with the sample compared to the 'population' and be sufficiently representative of the landscape's heterogeneity.

#### 3.2 Spatial-temporal variation

There are two major dimensions to consider when designing field campaigns: time and space. The temporal and spatial considerations must be adapted according to the ecosystem properties and the objective of the research project. There are roughly two main types of field campaigns: short-term intensive field measurements and long-term continuous measurements. Each type may have different purposes, including validation of discrete flight campaigns/satellite overpasses or focusing on capturing the seasonal dynamics and phenology of vegetation.

Results from the survey distributed to TRuStEE members showed that the spatial and temporal sampling strategy was deemed a critical aspect by 90 % and 80 % of the survey respondents, respectively (Fig. 8). However, survey results indicated a high variability of spatial sampling approaches undertaken by the distinct groups. For example, 60 % of respondents chose sampling points through a random distribution approach, whereas 40 % systemize sampling points based on environmental and/or vegetation characteristics. The sampling mode varied considerably between groups with 27 % of respondents sampling at fixed or changing multiple plots/points while 20 % sampled at a fixed single point/plot (Fig. 9a). The temporal sampling frequency also varied quite significantly among respondents, ranging from daily to yearly measurements (Fig 9b).





Figure 8. Survey results from respondents the most important aspects when designing field sampling protocols

Field measurements must be representative of the specific scale in question (*e.g.*, image pixel, ecosystem) where *in-situ* observations often need to be upscaled to represent larger footprints. The frequency and distribution of plots should be linked to the temporal and spatial resolution of the imaging sensor used and the scope of the study. For instance, Chuvieco *et al.* (2003) collected samples every 8 days to match the image acquisition dates of NOAA-14 AVHRR sensor to obtain a time series analysis for entire summer seasons. While Casas *et al.* (2014) concentrated on field sampling on numerous sites (39 different sampling sites) of varying cover types for three different dates within a maximum 2-day mismatch from remotely sensed image acquisition dates. Whereas a sampling rate of every 2 weeks is proposed for adequate seasonal and phenological considerations of herbaceous species in a Mediterranean ecosystem (Mendiguren *et al.*, 2015). Parameter specific constraints should also be accounted for as, for instance, in the case of EWT measurements (and other related water content parameters), temporal sampling scheme should assure that no rain has occurred in the previous 2 days to avoid superficial water over leaf samples (Mendiguren *et al.*, 2015).





In grassland and savannas, samples are generally extracted using random quadrants in plots. Chuvieco *et al.* (2003) detailed a field and laboratory protocol to measure field FMC for shrubs and herbaceous plants in a Mediterranean tree-grass ecosystem. In this study, samples were taken from five distinct 50 m x 50 m plots, where attempts were made to have nearly homogenous shrub or herbaceous cover at each plot. Studies tend to separate plots by homogenous cover type and place random sampling quadrants (Casas *et al.*, 2014; Ceccato *et al.*, 2002; Chuvieco *et al.*, 2003) and, if numerous species were present, the average per species per date was measured (Casas *et al.*, 2014; Chuvieco *et al.*, 2003).

In the case of the BigFoot project (Cohen & Justice, 1999) (), the sampling design was adapted to understand biosphere-atmosphere carbon fluxes at various spatial scales, which included validating Moderate Resolution Imaging Spectroradiometer (MODIS) products. This involved assimilating multi-scale data from *in-situ* measurements, eddy-covariance (EC) flux towers and remote sensing imagery (Landsat and MODIS). As such, 100 ground validation points were chosen in the field experimental site, with about 60-80 plots concentrated within 1 km radius of the site's flux tower to adequately characterize the vegetation properties within the tower footprint. Plot sizes



were designed as 25 m by 25 m to roughly correspond to a Landsat pixel and to be easily scaled to 1 km using nested increments.

The BIOSPEC project (<u>http://www.lineas.cchs.csic.es/biospec/</u>) took a similar approach in their field sampling design within their Mediterranean tree-grass experimental site. Three concentric zones around the main flux tower were adopted and plots (25 m by 25 m) were allocated randomly in each zone (with a minimum distance restriction between points). The number of plots in each concentric zone was based on the area of the respective zone and the distance from the tower. Nine, fourteen and eleven plots were allocated randomly in zones 1, 2 and 3, respectively, resulting in 34 plots in total (Fig. 10). This experimental site was designed with a multi-objective approach where field measurements can be related to various data sources (EC footprint, Landsat 30 m, MODIS 250 m, 500 m and 1 km) linking spectral, biophysical and flux information.

In the context of the BIOSPEC project, an analysis was performed to understand the number of plots needed for the adequate spatial characterization of the study site. Sampling plots were divided into two levels (1<sup>st</sup> order plots in green vs 2<sup>nd</sup> order plots in red as shown in Fig. 10). A statistical analysis was conducted to investigate whether biophysical field measurements were significantly (i.e., statistically) different between the two levels of plot groupings. A Mann-Whitney U test was performed on the monthly median biophysical values of LAI, fuel moisture content (FMC), equivalent water thickness (EWT) and above ground biomass (ABG) collected between 2009 and 2012. This is a nonparametric test, where no assumption of distribution is imposed, testing whether the two datasets have statistically different distributions and, thus, result from different populations. As such, field measurements grouped in level 1 plots (green points in Fig. 10) were compared against observations from the level 2 plots (red points in Fig. 10), investigating whether the two data groups were statistically different. Results of this analysis (Table 3) showed that the overall difference between the two sample sets (plots from 1<sup>st</sup> order vs 2<sup>nd</sup> order) were not statistically significant (to the 95% confidence interval). The null hypothesis, where both samples are subsets of the same population, was largely accepted. However, it was, rejected for AGB and FMC during May and June field campaigns, which indicated significant differences between these sets of plots during late springearly summer for those two variables. However, the overall indicator throughout the year demonstrated that both sample sets were not significantly different and only a marginal increase in information was being acquired by sampling both plot groups instead of just one.





Figure 10. Distribution of grass sampling plots in Majadas de Tiétar experimental site for BIOSPEC project

These analyses exemplified that the spatial sampling effort can be decreased without significant loss of information and still largely represent the spatial variance and heterogeneity of the study site. Since practical and logistical issues are crucial factors for the design of field campaigns, these types of analyses are recommended. This is notably important for long-term monitoring sites as it provides a greater understanding of how much data is required or considered appropriate to match objectives according to ecosystem characteristics.

The balance between temporal and spatial sampling intensity is another common predicament in the elaboration of field protocols. For certain ecosystems, seasonal changes may be more important than spatial variability (and vice versa). For example, Mendiguren *et al.* (2015) showed that, for a Mediterranean grassland, seasonal changes were more significant than their spatial variance. As such, they proposed a strategy to increase the sampling frequency in time but to lower number of plots sampled per day to more efficiently capture the variability of herbaceous water content (Mendiguren *et al.*, 2015).



Table 3. Results of nonparametric Mann-Whitney U-Test of biophysical measurements (EWT, AGB,	FMC, LAI)
comparing level 1 (N = 12) and level 2 (N=20) plots during BIOSPEC project	

EWT	March	April	May	June	October	November
U- Statistics (Mann-Whitney)	47	103	117	119	114	91
Z-Score	-1.116	-1.187	-0.691	-0.620	-0.449	-0.972
Sig. exacta [2*(Sig. unilateral)]	0.284	0.246	0.506	0.552	0.671	0.347
H <sub>o</sub> : Null hypothesis	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted
AGB	March	April	May	June	October	November
U- Statistics (Mann-Whitney)	52	80	53	71	124	97
Z-Score	-0.806	-2.002	-2.959	-2.321	-0.075	-0.734
Sig. exacta [2*(Sig. unilateral)]	0.446	0.046	0.002	0.020	0.956	0.481
Ho: Null hypothesis	Accepted	Accepted	Rejected	Rejected	Accepted	Accepted
FMC	March	April	May	June	October	November
FMC U- Statistics (Mann-Whitney)	March 50	April 76	<b>May</b> 52	June 32	October 93	November 82
FMC U- Statistics (Mann-Whitney) Z-Score	March 50 -0.930	<b>April</b> 76 -1.990	<b>May</b> 52 -2.995	June 32 -3.703	<b>October</b> 93 -1.235	November 82 -1.329
FMC U- Statistics (Mann-Whitney) Z-Score Sig. exacta [2*(Sig. unilateral)]	March 50 -0.930 0.376	April 76 -1.990 0.048	May 52 -2.995 0.002	June 32 -3.703 0.000	October 93 -1.235 0.228	November 82 -1.329 0.194
FMC U- Statistics (Mann-Whitney) Z-Score Sig. exacta [2*(Sig. unilateral)] Ho: Null hypothesis	March   50   -0.930   0.376   Accepted	April   76   -1.990   0.048   Accepted	May 52 -2.995 0.002 Rejected	June 32 -3.703 0.000 Rejected	October   93   -1.235   0.228   Accepted	November   82   -1.329   0.194   Accepted
FMC U- Statistics (Mann-Whitney) Z-Score Sig. exacta [2*(Sig. unilateral)] Ho: Null hypothesis LAI	March   50   -0.930   0.376   Accepted   March	April   76   -1.990   0.048   Accepted   April	May 52 -2.995 0.002 Rejected May	June 32 -3.703 0.000 Rejected June	October   93   -1.235   0.228   Accepted   October	November 82 -1.329 0.194 Accepted November
FMC U- Statistics (Mann-Whitney) Z-Score Sig. exacta [2*(Sig. unilateral)] Ho: Null hypothesis LAI U de Mann-Whitney	March   50   -0.930   0.376   Accepted   March   41	April   76   -1.990   0.048   Accepted   April   105	May 52 -2.995 0.002 Rejected May 108	June 32 -3.703 0.000 Rejected June 106	October   93   -1.235   0.228   Accepted   October   114	November   82   -1.329   0.194   Accepted   November   50
FMC U- Statistics (Mann-Whitney) Z-Score Sig. exacta [2*(Sig. unilateral)] Ho: Null hypothesis LAI U de Mann-Whitney Z-Score	March 50 -0.930 0.376 Accepted March 41 -1.488	April 76 -1.990 0.048 Accepted April 105 -1.116	May 52 -2.995 0.002 Rejected May 108 -1.010	June 32 -3.703 0.000 Rejected June 106 -1.081	October   93   -1.235   0.228   Accepted   October   114   -0.449	November   82   -1.329   0.194   Accepted   November   50   -1.659
FMC U- Statistics (Mann-Whitney) Z-Score Sig. exacta [2*(Sig. unilateral)] Ho: Null hypothesis LAI U de Mann-Whitney Z-Score Sig. exacta [2*(Sig. unilateral)]	March 50 -0.930 0.376 Accepted March 41 -1.488 0.148	April 76 -1.990 0.048 Accepted April 105 -1.116 0.276	May 52 -2.995 0.002 Rejected May 108 -1.010 0.326	June 32 -3.703 0.000 Rejected June 106 -1.081 0.292	October   93   -1.235   0.228   Accepted   October   114   -0.449   0.671	November   82   -1.329   0.194   Accepted   November   50   -1.659   0.103

An experiment, under the context of the BIOSPEC project, was undertaken to quantify the relative importance of sampling a greater number of plots (spatial variability), or rather sampling



more frequently in more dates (temporal variability) in a Mediterranean tree-grass ecosystem. The restricted maximum likelihood (REML) approach was used to estimate components of variance in sampling data. This method, similar to ANOVA, has the advantage of not depending on balanced data allowing for experiments to use different number of samples with heterogeneous variances (SAS Institute Inc, 2010).

Nine plots in Majadas de Tiétar experimental site were sampled in twenty separate occasions between 2009 and 2011 (April 7<sup>th</sup>, 2009 to April 14<sup>th</sup>, 2011). These data were used to understand the weighted contribution of different plots and different dates on the total variance. Results demonstrated that more than 55 % of variance was explained by the date (compared to about 16 % by plots) indicating that it was comparatively more effective to sample less plots in exchange for more dates (Table 4).

Random Effect	Var Ratio	Var Component	Std Error	95 % Lower	95 % Upper	Pct of Total
date_SI	1.9484062	0.0001836	0.0000721	0.0000423	0.000325	55.482
plot[date_SI]	0.5633909	0.0000531	1.9971e-5	1.3958e-5	9.2242e-5	16.043
Residual		9.4251e-5	1.496e-5	7.0641e-5	0.0001321	28.475
Total		0.000331	7.3466e-5	0.0002237	0.0005397	100.000

Table 4. Results of restricted maximum likelihood (REML) analysis

Spatial and temporal considerations are highly important when developing field protocols. Both dimensions must be appropriately represented by the field acquisition methods, particularly when upscaling to airborne/satellite pixel and/or depicting phenology (Held *et al.*, 2015). There is no obvious one-solution-fits-all method as each study site has unique characteristics. Experimental and statistical analyses, such as the examples discussed above, and even the implementation of a small-scale experiment as a pilot study case previous to a long-term monitoring experiment, may be a necessary first step to adequately understand the functioning of the system and optimize field acquisition protocols.

## 3.3 Ecosystem specificities

Distinct vegetation and ecosystem types have different specificities and challenges that make it difficult to generalize field protocols. The TRuStEE survey, even within a relatively small sample size, described four distinct ecosystem types, each with their own considerations and characteristics to acknowledge (Fig. 1). For instance, destructive sampling of short-stature ecosystems (*e.g.*, grasslands, croplands) have different implications compared to sampling in densely high statured or scattered tree ecosystems. In grasslands or short-statured vegetation, it is usually more viable to extract biophysical and structural parameters through harvesting/destructive methods. For example, LAI or biomass observations can be acquired by extracting all vegetation in a given quadrant area with the combination of laboratory analysis (*i.e.*, Casas *et al.*, 2014; Ceccato *et al.*, 2002; Colombo *et al.*, 2008). However, the use of optical or gap fraction methods, such as the LAI-2200 plant canopy



analyzer (LICOR Bioscience USA, 2011) may be limited by the plant height in grasslands and may not be a viable approach for understory species in heterogeneous sampling areas.

Harvesting methods of entire trees are generally complicated, although examples do exist (e.g., Nelson et al., 1999). In closed forests with relatively homogeneous vegetation height, optical sensors based on gap fraction (e.g., LAI 2200, Hemispherical Cameras) or gap size distribution (e.g., Tracing Radiation and Architecture of Canopies (TRAC) instrument) may be appropriate to accurately estimate LAI or plant area index (PAI), even though other issues may persist such as darkness, clumping, heterogeneous leaf angle distributions or multiple scattering within the canopy (Jonckheere et al., 2004). For individual leaf sampling from trees, a frequent method used is to climb the tree or have pole pruners to collect the most sunlit branches from the shaded and/or illuminated sides (de Jong *et al.*, 2014). These samples should be representative of the whole tree canopy, which may be complicated by the canopy structure, light conditions and species type. This is particularly important when upscaling leaf properties to represent whole canopy characteristics, a common procedure for vegetation remote sensing methods (*i.e.*, Zarco-Tejada et al., 2004). For example, Gond et al. (1999) discussed that temporal patterns of chlorophyll concentrations were significant between tree species but also within individuals, with large variations of chlorophyll between leaf samples observed. Depending on the measurement location on the leaf, chlorophyll concentration differed where a relatively decreasing gradient of chlorophyll concentration was observed between the tip and base of the leaf (Gond et al., 1999).

The selection of field measurement methods and instrumentation must also match the characteristics of vegetation species in question. For instance, the SPAD (Soil Plant Analysis Development) chlorophyll meter requires relatively large leaves in order for the instrument to work adequately, therefore it may only be appropriate for certain species. In some cases, instrumentation may need to be adjusted such as in Zarco-Tejada *et al.* (2004) where a custom-made port for an integration sphere was needed to accommodate the dimensions of typical olive tree leaves in order to measure its optical properties.

Field campaigns in dense or mixed forested study sites also need to carefully consider the density of diverse trees and the proportion of different species in a specific sampling area. Huber *et al.* (2008) sampled foliar biochemical components in three distinct study sites with varying plant functional types (needle leaf evergreen or broadleaf deciduous) and species in a mixed temperate forest. Sub-plots within study sites were selected based on homogeneity of functional type while sampled trees were chosen according to the similarities on neighboring species so that exposed crowns within pixel area were of similar species and chemistry as the target sample tree. One of the conclusions of the study noted that the differences in biochemical concentrations between the study sites were mainly driven by the differences in proportions of species in each site (Huber *et al.*, 2008). Remote sensing methods applied in forested areas need to also consider the influence of the understory on spectral and/or flux measurements. For example, Schneider et al (2014) simulated APEX imaging spectrometer data using a 3D radiative transfer model. The results indicated that by characterizing the understory using *in-situ* spectro-radiometric data, the simulated at-sensor radiance improved significantly compared to the APEX measured radiance.

In a tree-grass savanna or wooded grassland ecosystem, vegetation heterogeneity in time and space is a significant issue to consider when performing field measurements. These types of



landscapes have two main vegetation layers (trees and grass) that interact, while having significantly different structural and phenological properties. For instance, both Andreu *et al.* (2018) and Burchard-Levine *et al.* (2021) stressed the critical need to appropriately describe the different tree and grass characteristics (*i.e.*, canopy architecture, roughness and phenology) within energy balance models to accurately model water flux exchanges in a Mediterranean Oak savanna. As such, sampling design in tree-grass environments need to consider both types of vegetation in order to characterize the temporal and spatial variability, both vertically and horizontally, for the proper depiction of the ecosystem processes at the remote sensing level.

#### 3.4 Data organization and metadata

Data organization is a crucial component for the usability and long-term applicability of the acquired measurements. The local environmental conditions and the technical acquisition procedure often complicate the transferability of ground-based information. As such, measures for standardization would improve comparability and the long-term value of the acquired data (Pfitzner et al., 2011; Rüegg et al., 2014; Schweiger, 2020). Data organization, including metadata acquisition, is highly important for successful field campaigns, particularly when there is a long period between data acquisition and processing. For example, Schweiger (2020) suggested to develop a data management plan (DMP) for field campaigns, which integrate planning aspects in structured manner, ensuring the transparent and long-term sustainability of the project data. Chapter 3 of Australia's TERN technical handbook for field spectroscopy (Held et al. 2015) extensively discussed field data organization and management and is a global reference for these aspects. This initiative provided guidelines for the entire data management cycle including pre-field data management planning, infield data collection and post-field data storage and delivery. Data and metadata processing must be generated in function of the study objective and to understand the conditions of data acquisition (which may be useful to explain outliers or unexpected data). Protocols for data acquisition and processing are highly recommended to increase efficiency in the field and to have standardized output data formats. From the survey distributed within the TRuStEE network, 48 % percent of respondents organized their field measurements using digital spreadsheets and commercial tools while 61 % of respondents manually acquire measurement metadata using field logs (Fig. 11).





Figure 11. a) How survey respondents organize field data and b) method used to acquire metadata during field measurements

Different data levels (from raw to structured levels of processing) should be maintained to inspect and correct data, if needed. When possible, automation of tasks and systematic quality checks through programming are highly beneficial, especially for the standardization and consistency of data structures. In fact, 70 % of the TRuStEE survey respondents claimed to perform quality checks on the acquired data before using it.

Pre-defining sampling plots and file naming structure will aid in data sorting and can already give valuable information of the data file in question. As such, it is recommended to have standardized protocols at all levels of field measurements, from field acquisition to laboratory analysis and data processing. These protocols will systemize field campaigns and are valuable sources to maintain data acquisition and processing transparent and reproducible.

Organization of data to form databases is also highly important, particularly to ensure proper data sharing. For example, the SPECCHIO spectral information library (https://specchio.ch/) provides an extensive database and system for spectral data with the respective metadata set describing and complementing the acquired data. The data management system in SPECCHIO allows for the ingestion and processing of spectral information including the flexible expanding of metadata, adding to the standard metadata attributes. This allows for the homogenization of data and metadata, which grants for different user types with various applications. Database structures can also facilitate the grouping and querying of data by, for instance, geographical area and may be a useful tool to link various types of information together. Likewise, depending on the research line, it may be interesting to link both the spectral (*e.g.*, spectral indices) and biophysical (*e.g.*, LAI) data of the respective field site. The SPECCHIO spectral information system is a good reference on how to organize datasets and what type of metadata should be acquired. For proximal remote sensing measurements, Rasaiah *et al.* (2014) provided a critical study of the metadata needed for field spectroscopy across different disciplines. The study performed an international experiment involving a web-based survey and a panel of experts to identify the most important metadata needed to be acquired during field



spectroscopy. Results indicated 11 core fields: 'Viewing Geometry', 'Location Information', 'General Target and Sampling Information', 'Illumination Information', 'Instrument', 'Reference Standards', 'Calibration', 'Hyperspectral Signal Properties', 'Atmospheric Conditions and General Project Information' and additional metadata for vegetative surfaces include 'Species', 'Common Name', 'Leaf/Canopy', 'Height of leaf/canopy from Ground', 'Background (soil/other)', 'Leaf Angle Distribution', 'Evidence of Disturbance' and 'Visible Vegetation Stress Conditions' (Rasaiah *et al.*, 2014).

Mobile applications and tools may also help standardized the metadata collection during field campaigns using smartphones or tablets. For instance, the EpiCollect App system (<u>https://five.epicollect.net/</u>), developed and maintained by the Imperial College of London, can be used to generate forms for metadata collection using mobile devices. Data is collected including GPS location and media are stored on a central server, which can be revised through maps, tables or charts. Another example is the Open Data Kit (ODK, <u>https://opendatakit.org/software/</u>), which is an open-source package developed by Google and the University of Washington to create field data forms with mobile devices. These types of tools are very useful to manage projects and associated metadata as different users can add entries in a collaborative and systemic manner. Refer to Chapter 3 and 4 of Held *et al.* (2015) and Schweiger (2020) for further general guidelines and recommendations when designing data management and organization systems for remote sensing-based field campaigns.

#### 4. Summary and Conclusions

Field observations are an essential, albeit often overlooked, aspect of remote sensing studies. Several references provide comprehensive guidelines for field spectroscopy, however much less information is available recommending best practices for *in-situ* collection of biophysical variables or plant traits, especially those intrinsically linked to remote sensing applications. While many protocols are available in the literature, they are often scattered in references focusing on different disciplines (e.g., ecology vs agriculture vs micrometeorology) or are limited to specific projects or geographies. This article reviewed the most common references for plant trait protocols and datasets currently available and highlighted certain recommendations to consider when designing a field experiment and campaign related to the remote sensing of vegetation. Importantly, statistical analyses, such as those described above, can help to frame an experimental design that ensures sampling plots have an appropriate spatial-temporal scale that fit the project objectives, including balancing a sufficient sample size with logistical/economic costs. The survey among TRuStEE members provided a snapshot of the current field practices being undertaken by the remote sensing of vegetation community in leading European institutions with expertise on ecosystem modelling, plant physiology and remote sensing. This review demonstrated the importance of in-situ data collection standards of plant traits in remote sensing. Further work is needed to improve the standardization of data collection, management and processing to ensure a greater long-term transparency, sustainability and reproducibility of both plant traits and spectral observations from multiple scales.



## 5. Acknowledgements

The research received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie TRuStEE project (grant agreement No 721995). It was also funded by the Spanish Ministry of Science through the BIOSPEC CGL2008-02301 project and the Ministry of Economy and Competitiveness through FLUXPEC CGL2012-34383 and SynerTGE CGL2015-G9095-R (MINECO/FEDER, UE) projects. The research infrastructure at the measurement site in Majadas de Tiétar was partly funded through the Alexander von Humboldt Foundation, ELEMENTAL (CGL 2017-83538-C3-3-R, MINECO-FEDER) and IMAGINA (PROMETEU 2019; Generalitat Valenciana). We would like to thank all people involved during the field campaigns throughout the years from different institutions: CSIC, INIA, UAH, CEAM, MPI-BGC, UEX and UNIZAR.

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