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**To cite this version:**

Christian Perennou, Anis Guelmami, Marc Paganini, Petra Philipson, Brigitte Poulin, et al.. Mapping Mediterranean Wetlands With Remote Sensing: A Good-Looking Map Is Not Always a Good Map. Advances in Ecological Research, 2018, 58, pp.243-277. 10.1016/bs.aecr.2017.12.002 . hal-02191341

**HAL Id: hal-02191341**

**https://hal.science/hal-02191341v1**

Submitted on 23 Jul 2019

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# Mapping Mediterranean Wetlands With Remote Sensing: A Good-Looking Map Is Not Al
# Map

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How to cite : Perennou C., Guelmami A., Paganini M., Philipson P., Poulin B., Strauch A., Tottrup C., Truckenbrodt J., Geijzendorffer I.R. 2018. *Chapter Six - Mapping Mediterranean Wetlands With Remote Sensing: A Good-Looking Map Is Not Always a Good Map*.David A. Bohan AJD Guy Woodward and Michelle Jackson, editor. Advances in Ecological Research 58:243–277. doi: 10.1016/bs.aecr.2017.12.002

Abstract

Wetlands are a key habitat within the Mediterranean biodiversity hotspot and provide important ecosystem services for hum Remote sensing (RS) has significantly boosted our ability to monitor changes in Mediterranean wetlands, especially in areas w information is being collected. However, its application to wetlands has sometimes been flawed with uncertainties and unrec large extent due to the inherent and specific ecological characteristics of Mediterranean wetlands. We present here an overv the art on RS techniques for mapping and monitoring Mediterranean wetlands, and the remaining challenges: delineating and habitat types; mapping water dynamics inside wetlands; and detecting actual wetland trends over time in a context of high, n most important lessons learned are that ecologists' knowledge need to be integrated with RS expertise to achieve a valua approach of these ecosystems.

## 1. INTRODUCTION: THE CHALLENGES OF MONITORING WETLANDS STATUS AND TRENDS WITH REMOTE SENSING (RS) DATA

Mediterranean wetlands are part of a global biodiversity hotspot, hosting many endemic species (e.g. Darwall et al., 2014). Their global importance stretches further as they produce a global share of the ecosystem services that is greater than their relative habitat extent (Zedler and Kercher, 2005). With current decreasing trends in natural habitat extent and regionally increasing human population numbers (MWO, 2012a), the importance of the remaining, increasingly threatened Mediterranean wetlands will only further increase. The importance of Mediterranean wetlands is acknowledged in multiple Multilateral Environmental Agreements (MEAs), especially the Ramsar Convention (e.g. Gardner et al., 2015; Ramsar Convention Secretariat, 2015), one of the most influential agreements for the conservation of wetlands globally. The monitoring of changes in Mediterranean wetland state and extent therefore provides crucial information for decisions makers and feeds into a diversity of policy reporting activities at different spatial scales (e.g. Beltrame et al., 2015; MWO, 2012a, b, 2014; Perennou et al., 2016; Plan Bleu, 2009).

The use of satellite imagery for wetland inventories and monitoring offers a great potential because of repeated, homogeneous coverage of large areas (e.g. Dadaser-Celik et al., 2008; Ozesmi€ and Bauer, 2002; Rebelo et al., 2009; Rosenqvist et al., 2007). The production and interpretation of wetland habitat maps have gone through a steep learning curve, leading to a wide diversity of available products (Guo et al., 2017). The emergence of new satellites offers possibilities to further improve our understanding of changes in wetlands. The Sentinels of the European

Copernicus Program form a recent initiative, which provides free optical and radar observations at a high spatial resolution (10-20 m) and short revisiting time. All technical improvements will potentially allow us to better distinguish different wetland habitats.

However, this is also a moment where progress already made can be easily lost as new RS tools and new mapping nomenclatures have to be developed for the new satellite data. International cooperation and collaborative development of RS methods, guidelines and best practices are required to avoid duplication of efforts, foster progress and innovation, and provide long-term access to the developed products, methods and tools. The new GEO-Wetlands initiative of the Group on Earth Observations (GEO) addresses this requirement and several of the projects contributing to this chapter form a part of this initiative.

This chapter presents the improvements in the monitoring of Mediterranean wetlands using RS, starting from the end of the 80s, when the first maps based on CORINE land cover (CLC) (Bossard et al., 2000) were produced, up to the most recent monitoring efforts of 2016. It should be emphasized that many of the issues that will be covered are not Mediterranean specific, but rather are specific to (semi)-arid regions. Ephemeral wetlands, rice paddies, artificial wetlands, irregular precipitations, all occur across the globe, and our Mediterranean review should thus be seen as a regional case study with lessons that are applicable globally. We use this overview to raise awareness of the challenges of using RS to monitor wetland habitats, some of which have still to be embraced. The most crucial recommendation for advancing our capacity to use RS for the monitoring of Mediterranean wetlands is that iterative exchanges between wetland ecologists, hydrologists and RS experts are necessary for obtaining credible results (e.g. Skidmore et al., 2015).

To be able to reflect on our capacity to monitor Mediterranean wetlands, we first present three of their characteristics that are drivers of their rich biodiversity, but that also generate challenges for monitoring change. Of course there are common general challenges related to the mapping of wetland habitats using RS data, but here we focus on those that particularly affect wetlands in arid and semiarid areas such as the Mediterranean. The true specificities of this region, e.g., how wetlands are classified for management purposes under local, regional and international legislation on wetlands, or how nomenclatures have led to over- or underestimation of regional habitats, do not lessen the applicability of most lessons to other bioclimatic regions too. Finally, we emphasize that many of the challenges reviewed below have either been addressed recently, or will be discussed further in Sections 2-4, with suggestions on how to address them.

## 1.1 Characteristic 1: Wetland Habitats and Surface Water Dynamics

The Ramsar Convention takes a broad approach in determining the wetlands which come under its mandate. In the text of the convention (Article 1.1), wetlands are defined as: “areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed six meters” (Ramsar Convention Secretariat, 2013).

These different wetland types have a variable level of detectability using RS data and, therefore, their identification, delineation and monitoring are challenging from a pure RS point of view. In particular, there is a frequent confusion between flooded areas (or surface waters) and wetlands in RS studies, despite their major ecological difference: some wetlands are only rarely and partly flooded, whereas many non-wetland habitats (e.g. agricultural or forest) can occasionally be flooded. For example, the GIEMS dataset (Global Inundation Extent from Multi-Satellites) and other measurements of surface water are frequently assimilated to wetland extents (Aires et al., 2013; Fluet-Chouinard et al., 2015; Papa et al., 2006; Prigent et al., 2001, 2012). These two essential metrics are in fact quite distinct, as national statistics for Mediterranean countries show (Fig.1), and confusing them may lead to underestimations or overestimations of the total amount of wetland habitats.

One of the main reasons why RS tools often underestimate the extent of wetland habitats is that the spatiotemporal dynamics of flooded areas are difficult to tackle, even with good time series. For instance, some ephemeral wetlands are rarely flooded and are often missed by RS datasets recording "surface waters." Conversely, identifying and delineating flooded areas under a dense vegetation canopy are crucial for the monitoring of several Red List habitats, but still difficult to assess using optical RS data, where the presence of water is not easily detected under dense emergent vegetation (see Section 3.2 for some possibilities offered by new Synthetic Aperture Radar (SAR) data).

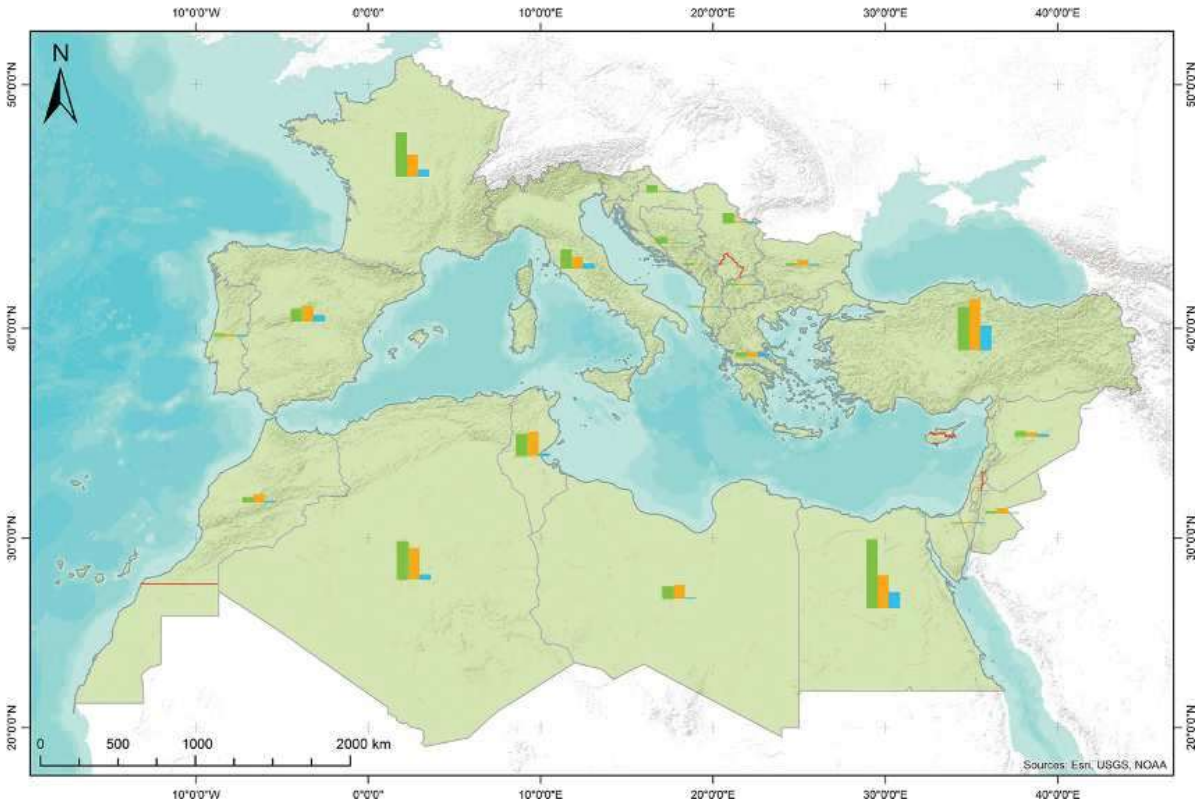


**Figure 1: Comparison between national estimates of total wetland surface for Mediterranean countries (Mediterranean Wetland Observatory, green; after Perennou et al., 2012; Global Lakes and Wetlands Database, brown; after Lehner and Döll, 2004) and surface waters (Global Surface Water, blue; after Pekel et al., 2016).**

As a result, what is often mapped as "flooded areas" are in fact only the "open water areas," leading to an underestimation of the real flooded areas. Fig. 2 illustrates a lake in Algeria mapped using the Global Surface Water dataset, a Landsat-based approach using optical data (Pekel et al., 2016) where parts that are temporally flooded are indicated as dry for more than 30 years (from 1984 to 2015). This is contrary to local ecological knowledge of this well-known Ramsar site (Saifouni and Bellatreche, 2014). The reason is simple: dense aquatic vegetation hinders the detection of truly inundated areas.

## 1.2 Characteristic 2: Artificial vs Natural Wetland Habitats and Their Relevance for Biodiversity

Wetland habitats, hydrology and water quality have been thoroughly manipulated by humans for centuries so wetlands that are strictly "natural" in their functioning are rare. It is therefore challenging to draw the line

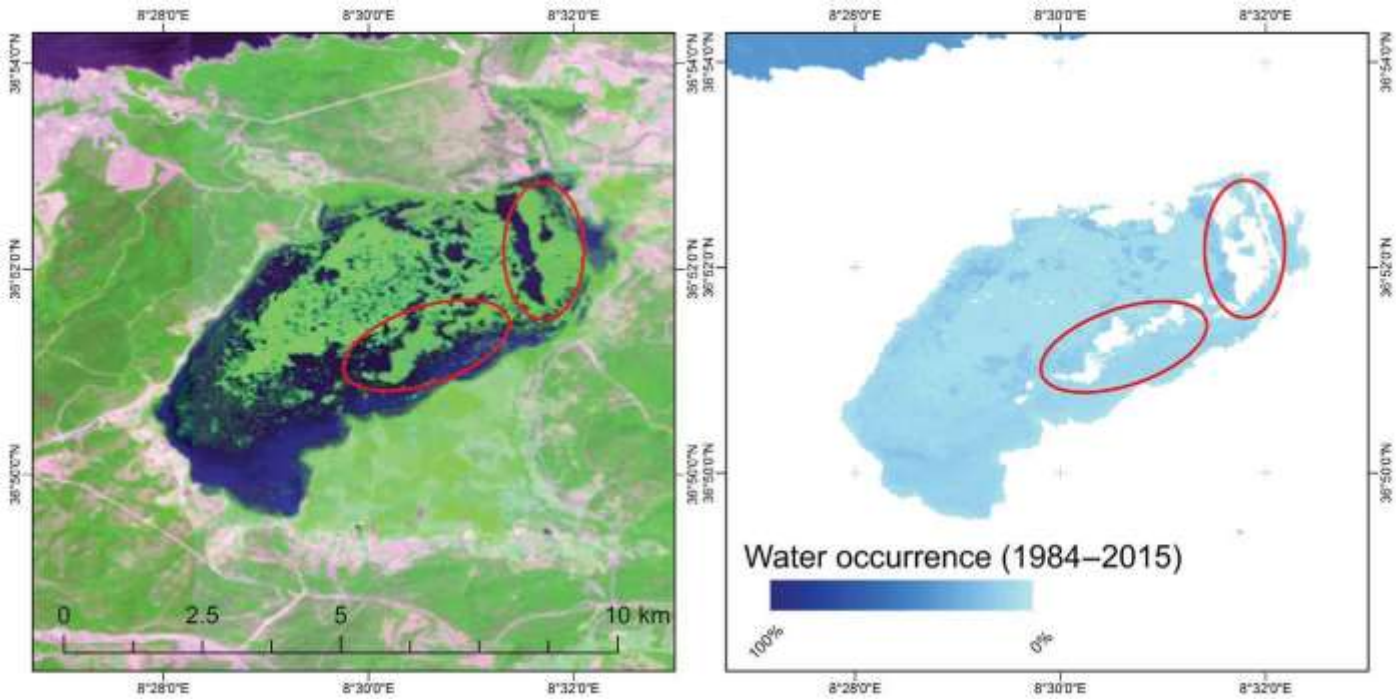


**Figure 2: (Left) Landsat-8 image 2015-05-12 for Tonga Lake (R/G/B: SWIR/NIR/R), in Algeria. (Right) Water occurrence map. The water occurrence map would suggest that part of the wetland was never flooded between 1984 and 2015 (areas in white within red circles) despite that local experts identified these areas as temporarily inundated during this period and covered by dense aquatic vegetation(SaifouniandBellatreche, 2014). Left: Landsat 8 image: Courtesy of the U.S. Geological Survey. Right: The Global Surface Water dataset, produced from Landsat remote sensing data (after Pekel et al. 2016).**

between "natural wetlands" and "artificial wetlands," given that many intermediate situations exist, e.g., very old modified wetlands that have reverted to a "near-natural" state in terms of habitats, while still having a strongly man-modified hydrology and water quality. Despite this difficulty, ecologists routinely use the distinction "natural" and "artificial" (e.g. Sebastian-Gonzalez and Green, 2016).

One of the main reasons for the monitoring of Mediterranean wetlands is to obtain estimates of changes in habitat extent and related impacts on biodiversity. Of all the species that Mediterranean wetlands host, an important part is endemic and many Red List species depend on natural wetland habitats (MWO, 2012b; Riservato et al., 2009). Artificial wetlands host a significantly lower biodiversity (e.g. Sebastian-Gonzalez and Green, 2016), and it is therefore important to be able to separate them reliably from natural wetlands (e.g. distinguishing a natural lake from a reservoir; a natural lagoon from a salina). But, in practice, telling the difference based on RS data alone is not always possible. Use of object-based classifications or of a predefined matrix to discriminate natural from man-made wetlands have been proposed (Camilleri et al., 2017). However, natural and artificial wetlands are often similar in shapes and updating an artificial wetland matrix can pose a problem for routine monitoring over large geographical scale comprising several hundreds of sample sites. Finally, and related to artificialization, water quality too has a profound impact on biodiversity, and RS monitoring methods are making progress (e.g. Brezonik et al., 2005; Ritchie et al., 2003; Sandstrom et al., 2016; Tyler et al., 2006; Vihervaara et al., 2017).

### 1.3 Characteristic 3: Strong Inter-and Intra annual Variability

The rate with which changes take place and the variability of water availability in wetlands in arid or semiarid regions such as the Mediterranean is a challenge for the detection of long-term trends. Although some changes take place rapidly and are relatively easy to detect (e.g. construction of a dam), others are slower and show greater variation over time (e.g. reduced water availability due to climate change, or agricultural land abandonment transforming it back gradually into a "natural" wetland), making it difficult to distinguish when a site has definitely changed or is "only" temporarily affected.

Mediterranean climate conditions vary irregularly within and between years. In the driest areas of North Africa, large wetlands (e.g. chotts and sebkhas) can remain virtually devoid of water for years, and refill irregularly depending on erratic rains. Assessing the boundaries of such wetlands through RS poses challenges, since long time series of images may be required to capture the full, potential extent of a given wetland, independently from its highly variable level of filling. Images that by chance focus on a dry period may be prone to misinterpretation as "severe reduction in the wetland size". Long-term, slow changes like the impact of declining precipitation are difficult to detect under such highly variable conditions and a reduction in wetland extent even more so. Clouds, which bring precipitation and refill wetlands, are an additional, frequent obstacle to obtaining good time series of satellite images, and may hinder the detection of flood extent in crucial periods.

Based on these characteristics, many of which are common to other arid and semiarid regions beyond the Mediterranean basin, we can identify three challenges for the use of RS to monitor trends in Mediterranean wetlands: (1) the delineation and separation of habitat types; (2) the mapping of the water dynamics inside wetlands; and (3) the detection of trends over time with respect to a naturally occurring variability.

In the next sections, we demonstrate how these challenges have previously led to errors in the interpretation of RS data for Mediterranean wetlands monitoring, how some challenges have been recently overcome and which other ones remain to be addressed. Table1 presents a schematic guide to how these issues will be covered.

## 2. DELINEATION AND SEPARATION OF HABITAT TYPES

Temporal detection of changes in habitat type and extent of Mediterranean wetlands first requires that the delineation and separation of habitat types is consistent over time. Second, to determine the nature of the changes, the methods and nomenclature need to be constructed coherently. Key elements for delineating and mapping wetlands using RS are quality images; rules for detection of significant changes in wetland habitats; a wetland nomenclature; procedures for interpreting habitat classes; and robust validation procedures. Despite precautions, land cover misclassifications always occur (Kleindl et al., 2015), and a known margin of error is usually accepted by specialists. However, known and unknown type errors can easily outweigh the credibility of habitat maps if the mentioned key elements are not carefully developed and implemented. Known and unknown errors can be caused by intrinsic technical limitations, human errors, or an interaction of both. Misclassifications can be significantly reduced when local knowledge and ecological expertise of Mediterranean wetlands are combined with technical RS expertise.

**Tableau 1: Schematic of the Challenges Posed by Wetland Remote Sensing and of Some of the Solutions Currently Applied**

| Inherent Characteristics of Wetlands in Arid Regions Such as the Mediterranean That render the Interpretation of RS information Difficult | Progress Made to Date | Remaining Challenges |
|---|---|---|
| Intertwined wetland habitat and surface water dynamics | – Increased knowledge on uncertainties | – Quantification of uncertainties for habitat changes |
| | – Increased number of images per year | **– Retroactive studies (to periods with fewer images)** |
| | – Improved habitat classification at local scale | – Decision rules for habitat classification at large, multisites scale |
| | | **– Integration of ecological knowledge with technical know-how** |
| | | – Improved nomenclature based on dynamics as characteristics (trade-off between more classes and more confusion risks) |
| | | – Improving semantics: wetlands vs flooded areas vs open waters |
| | | **– Application of existing validation procedures** |
| ) Artificial vs natural wetland habitats and their relevance for biodiversity | – Object-based classifications | – Application to large wetland samples |
| | | – Water quality assessment beyond a few pollutants |
| i) Strong inter- and intraannual variability | – Increased number of images per year | – Separating long-term trends vs annual variability in flooding |
| | | **– Detection of water under vegetation** |
| | | – Detection of ephemeral wetlands |

Remaining challenges in bold are applicable to more than one of the characteristics in left column, but are only mentioned once.

## 2.1 Wetland Habitat Nomenclature

To produce maps for habitat monitoring derived from optical RS data, a nomenclature is required to identify and delineate separate habitats. Ideally the nomenclature consists of classes that are both ecologically relevant and distinguishable with optical RS data. In the absence of a satisfying standardized nomenclature for Mediterranean wetlands, most initiatives developed their own, which has led to a multitude of nomenclatures with varying degrees of applicability at different scales and geographic regions (Tomaselli et al., 2013). For instance, the GlobWetland-II (GW-II) ESA project (GlobWetland-II, 2012) developed a hybrid hierarchical typology between the European Union's CLC (European Commission/JRC and EEA, 1997) and the Ramsar Convention's nomenclature (Ramsar ConventionSecretariat,2010).Whereas CLC encompasses all classes of land cover to be found in Europe with only 11 classes being predominantly wetlands, the Ramsar typology(Ramsar Convention Secretariat,2010)provides ecologically relevant and detailed descriptions of wetlands comprising 42 classes, but does not cover other habitats, which are out of the scope of the Ramsar Convention. Another example of hybrid classification developed for specific purposes is from the Horizon-2020 SWOS (Satellite-based Wetlands Observation Service) project that combines the hierarchical Mapping and Assessment of Ecosystem Services (MAES) nomenclature with wetland classes to monitor their potential for ecosystem services.

When nomenclatures do not contain many wetland-relevant classes, such as the much used CLC in European countries, a significant part of wetland habitats can go undetected as they are merged with larger (e.g. agricultural) classes. This was for instance the case in France where wet meadows, nationally one of the most important wetland types in terms of area, ended up being lumped with dry meadows in CLC, and therefore not identified as "wetlands" in the final maps (Perennou et al., 2012).

From an ecological point of view, a more detailed nomenclature is appealing because its application may provide better estimates of biodiversity and ecosystem services. However, use of ancillary data is then necessary to produce reliable maps from RS data. Ancillary data may include preexisting local land cover maps, in situ data, literature, VHR images and contextual data (e.g. topography, hydrology, precipitations). Collecting this information may be realistic when working at the scale of a site level or for a limited number of habitats, but less feasible at large scales. For instance, of the 103 different classes developed in GW-II, the 55 classes for wetlands comprised many classes that

eventually proved difficult or even impossible to segregate using RS data alone. In theory, the hierarchical structure should have allowed mapping at higher level only, when the information available did not allow separating finer (lower-rank) classes. However, in practice, the lack of ancillary data often translated into detailed maps of high uncertainty although confusion matrices (see below) were developed. Unfortunately, this uncertainty is rarely estimated when mapping biodiversity and ecosystem services (e.g. Rocchini et al., 2011), resulting in visual representations that may be powerful, but include lots of unacknowledged errors (Hauck et al., 2013). This should eventually be overcome by not placing on the mapping operators any pressure for always having final results using the most precise habitat type level, rather accepting maps with less precise classes that are more accurately mapped. This could be done by aggregating habitat types into broader classes(higher levels in hierarchical nomenclatures),when dealing with regional assessments involving many sites and limited ancillary data. Aggregating land cover categories into less numerous classes has been shown to increase thematic map accuracy (Kleindl et al., 2015), thereby reducing the classification errors and increasing time efficiency for multiple sites assessments(e.g. MWO,2014).However, it also reduces the capacity to monitor specific habitat transformations at wide scales, which is the main interest of using RS data. In addition, coarse land cover categories are likely to provide insufficient information if the maps are to be used to inform management decisions. Clearly, an overarching, hierarchical nomenclature is needed to make both local and broad-scale assessments, but deciding on the most relevant level of detail to use needs to be carefully set depending on the scale of the work (local vs regional) and the purpose for which the map will be used, and taking into account the necessary trade-off between more classes and more confusion risks.

Another approach that is particularly useful to document habitat transformation consists of using the Earth Observation Data for Habitat Monitoring (EODHaM) system developed by Lucas et al. (2015). Using the hierarchical land cover classification system(LCCS)from the Food and Agriculture Organization (FAO), this approach uses a combination of pixel and object-based procedures. The first four levels of the FAO LCCS can be obtained based on simple rules that can be quantified by RS: vegetated vs non vegetated areas, herbs vs trees, terrestrial vs aquatic, cultivated vs natural, etc. Combined with expert local knowledge (e.g. available land cover land use maps), these methods are also applicable to other nomenclatures (e.g. EUNIS, Annex I) for generating habitat maps. An additional module quantifies changes in the LCCS classes and their components, being particularly useful to monitor ecosystem evolution and support decisions relating to the use and conservation of protected areas, including wetlands.

## 2.2 Quality Images

Distinguishing different wetland types or wetlands from other habitat types based on satellite images often requires several scenes from contrasting seasons. This is the case for instance for separating ricefields (which are artificial wetlands) from dry crops or from reedbeds (natural wetlands), since the seasonalfloodingregimeorplantphenologyarekeycriteriatodistinguishthese habitats. The initial Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) data had intrinsic limitations in temporal resolution, which limited the detection and interpretation of wetlands. In some areas, a too low image frequency for previous time periods (e.g. during the 80s and before)increased the probability that over a given year, no cloud-free images would be available which is a challenge especially in the rainy season. This leads to incorrect habitat mapping caused by omission errors (when a habitat is left out of the category being evaluated) or commission errors (when a habitat is incorrectly included in the category being evaluated).

Several solutions have been tested to overcome these misclassifications, each with their own limitations. For instance, periods over which RS images are used were extended, sometimes up to 2 years around official dates, to acquire enough satellite scenes at different seasons (GlobWetland-II, 2011).This however reduces the variability that can be detected over shorter time scales. Another approach, which has become available recently, is the inclusion of higher frequency images, e.g., SAR data from Sentinel-1 and optical data from Sentinel-2, which will certainly be useful for reducing the error rates due to image availability.

To reduce the unknowns when not enough ancillary data are available, mapping can focus on broad habitat classes encompassing gall those that cannot be separated (e.g. “water bodies” instead of “natural lakes” vs “man-made reservoirs”) (Mediterranean Wetlands Observatory internal protocol). This approach, however, will not permit the detection of all habitat transformations that take place.

To improve the accuracy of habitat delineation, especially for retrospective analysis, the number of images can be increased. New technologies, such as Sentinel can provide a higher number of images in a shorter time span, but to have a similar number of images for a date in the past requires searching for images at such a very large range around the intended date (e.g. sometimes ± 2 years in the case of GlobWetland-II, 2012) that interand intraannual variation can no longer be distinguished. While this approach is reasonable for detecting and delineating natura habitat types that are unlikely to change much over a few years, it leads to systematic over estimations of specific habitat classes in agricultural landscapes with a highcrop rotation frequency, such as rice. Flooded fields that are used for rice production are counted as wetlands and by aggregating images of multiple years,the total surface covered with (flooded) rice fields in any year is summed up, rather than averaged. This can lead to an overestimation of rice fields up to three times their actual surface, e.g., in CLC (Perennou et al., 2012). However, the availability of new optical and SAR RS data with very high temporal resolutions (Landsat-8, Sentinel-1 and Sentinel-2) allows to better capture interannual dynamics of habitats such as ricefields (Fig. 3).

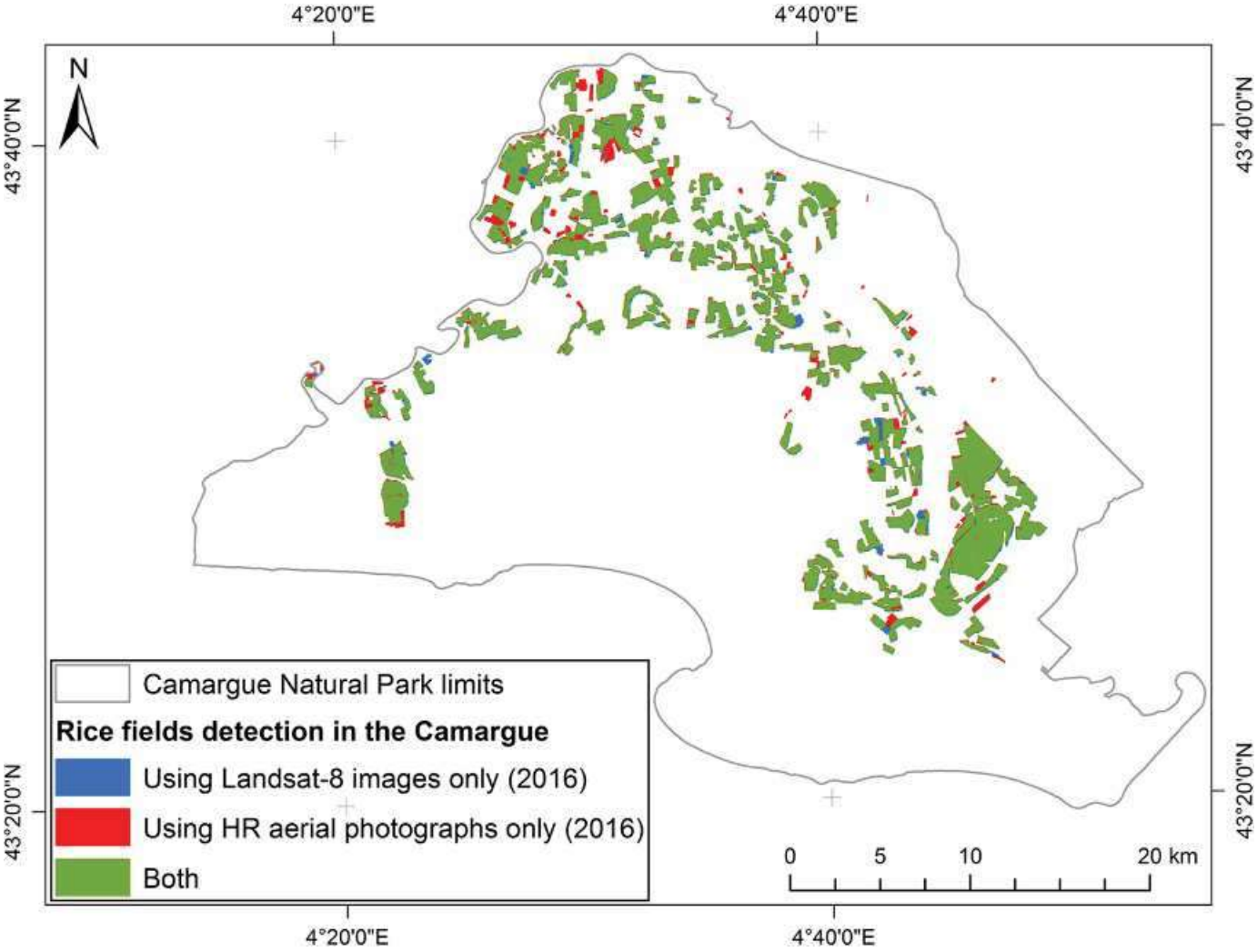


**Figure 3: Comparison between two different methods delineating rice fields in the Camargue in 2016 an object-based classification of 8 Landsat-8 (L8) images covering the whole hydroperiod and using the GEO classifier software developed by the SWOS project (total rice fields area ¼ 11,201ha); and a “field reality” consisting of a land cover map provided by the Regional Natural Park management body, based on aerial photographs interpretation (total rice fields area ¼ 10,694ha). Rice field areas are almost the same, with a little overestimation for the L8-derived map (90% of existing rice fields are detected using L8 images).**

## 2.3 Procedures for Interpreting Habitat Classes

Technical experts that create RS maps are not necessarily familiar with all the (wetland) habitat types and wetland ecology. Therefore, field data are crucial for training and validating maps, as are explicit guidelines for identifying and reducing supervised classification omission and commission errors, and obtaining comparable results from different operators. These guidelines should include explicit decision rules on how particular habitat types should be separated, their flooding calendar, vegetation phenology and how/ when/what ancillary data would best assist the mapping, considering which habitat types are commonly confounded in the Mediterranean. They should also assist with what to do in borderline cases, i.e., situations where the habitat delineation and identification can lead to two different habitat type interpretations, both being valid from different wetland perspectives. For instance, decreasing water levels in a man-made reservoir will expose banks that, when covered by aquatic vegetation, appear very similar to natural marshes and could be mapped as such. In a dry year, the falling water levels in a reservoir may consequently be misinterpreted as a decrease in man-made reservoir habitat coupled with an increase in (natural) marshes (e.g. MWO, 2014). Such decision rules are clearly a much needed avenue for future research, and developments are ongoing but remain so far unpublished.

In summary, when human decisions are required to produce accurate maps, clear, detailed and explicit guidelines and training data will enhance map quality by reducing both the variability between individual mappers, as well as reducing classification errors. This in turn greatly increases the replicability of results.

## 2.4 Validation Procedures

Despite having diligently applied nomenclatures using the best available RS and ancillary data with interpretation protocols, errors can still occur (Kleindl et al., 2015; see also Box 1). To keep them within acceptable limits, the produced maps should always be checked and validated. This process of validation can rely on comparing the produced maps with “reality” by using spatially and temporally specific reference material, combined with a critical, independent assessment based on wetland ecology expertise.

For land cover maps, the ideal situation is an in situ (field) information verification at a date sufficiently close to the satellite image(s) used, but RS-derived maps can also be compared with other independent and more accurate maps, such as often produced by local management bodies, usually based on a higher spatial resolution data and integrating more complex thematic details, or with some regional wetland inventories (e.g. Congalton, 1991; Fluet-Chouinard et al., 2015; Sanchez et al., 2015). Known borderline cases and clusters of often confused habitat types can be reviewed by wetland experts to further decrease uncertainties in habitat identifications. In addition, wetland experts can easily detect some habitat identification errors bycomparing produced maps or their trends over time. For instance, after a dam is built on a river and the reservoir fills up, the habitat behind the dam should be identified as a “human-made reservoir/lake” and should not be identified as an (expanding) “river habitat,” i.e., a natural wetland type (Fig. 4).

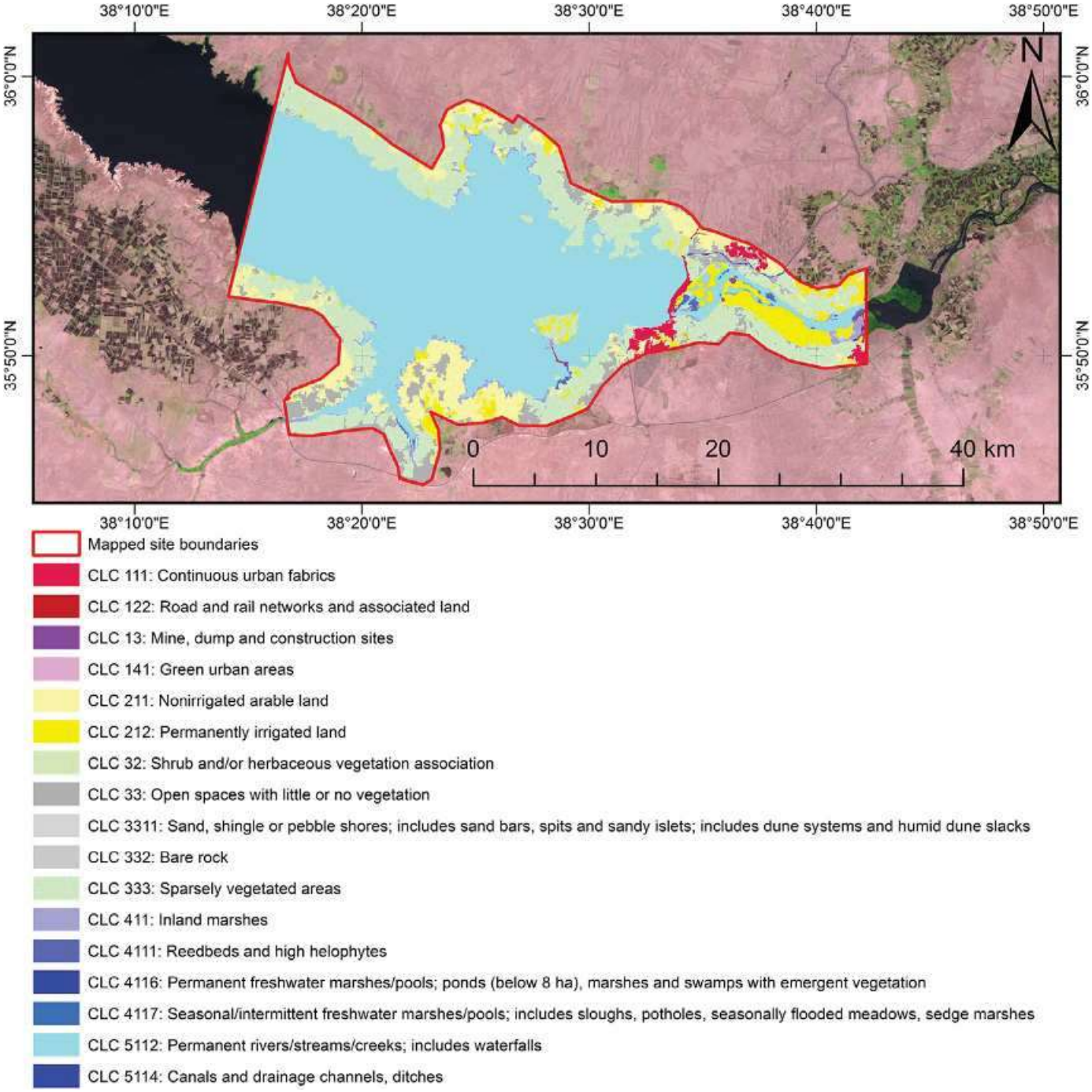


**Figure 4: A typical error affecting the largest man-made wetland in Syria: Al-Assad reservoir on the Euphrates, mapped as a "Permanent river." Background: Landsat TM 200606-24 (R/G/B: SWIR/NIR/R). Data from GlobWetland-II, 2014. GlobWetland-II, a regional pilot project of the Ramsar Convention on Wetlands: handbook. GW-II project documentation. Jena Optronik, Jena, Germany. 110 p. http://www.globwetland.org/.**

## *BOX 1 A Quality Control Exercise of Mediterranean Wetland Mapping Using RS Data—The GlobWetland-II Case Study*

The GlobWetland-II (GW-II) project (ESA DUE project, 2010–14) aimed at producing a homogeneous assessment of 284 wetlands spread all over the Mediterranean region (Fig. 5) and their change over time (1975–1990–2005), using Landsat imagery. The approach followed in the project accumulated uncertainties due to many of the challenges presented in this chapter. In this box, we present an analysis of the Mediterranean Wetlands Observatory (internal document) in which we quantified the errors of the habitats mapped in the GlobWetland-II project. The quality control consisted of the scrutiny of the database on three possible inconsistencies: (1) unrealistically large changes in habitat surface; (2) uncommon transitions in habitat types; and (3) mismatch of the habitat type identification with habitat type observations from the field, the literature and the Ramsar database. These three inconsistencies are partly based on insufficient ecological understanding of the Mediterranean wetlands and partly based on a too general understanding of the mapping of habitat changes. The quality control weapplied therefore typically represents an integration of technical and ecological knowledge that can greatly reduce uncertainties in RS monitoring of (Mediterranean) wetlands.

The quality control assessment showed that, in the initial analysis, errors with an absolute value of over 1000ha of "Natural wetland areas" occurred on c.24% of all sites in at least one of the years; misclassifications of more than

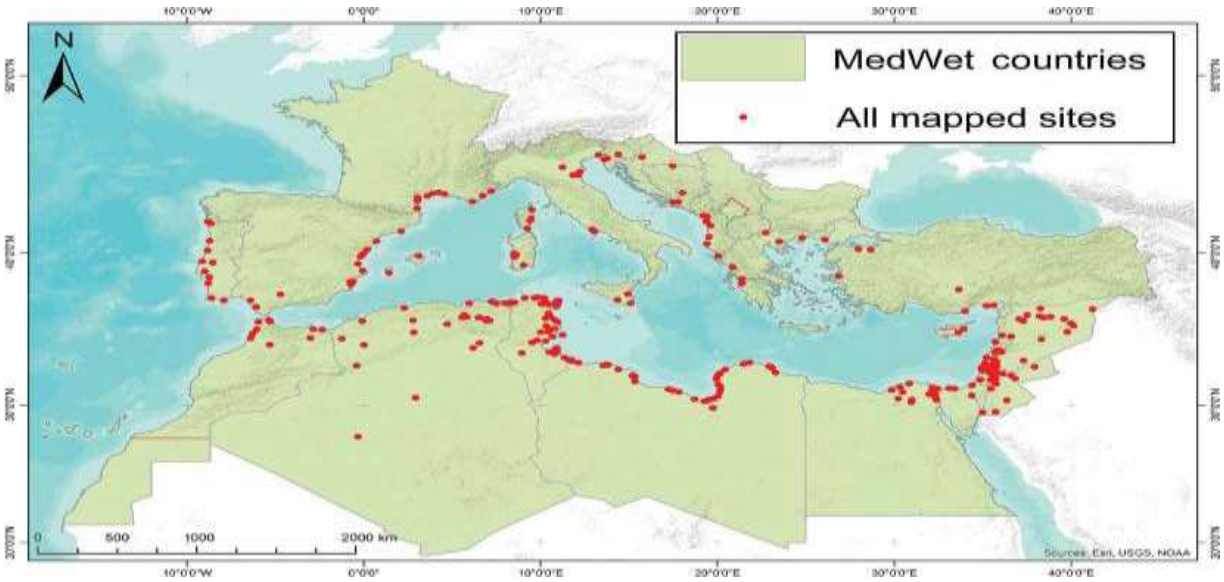


**Figure 5: Distribution of the GlobWetland-II project sites.**

### *BOX 1 A Quality Control Exercise of Mediterranean Wetland Mapping Using RS Data— The GlobWetland-II Case Study— cont'd*

10,000 ha of natural wetlands were found on 5% of the sites, and two sites had more than 100,000ha of natural wetland areas incorrectly classified. To put these numbers in perspective, a total of 1.97 million ha of natural wetland habitat was mapped in the Mediterranean region across the 284 sites in 2005. The misclassifications generated both under- as well as overestimations (Fig. 6) and were not systematic. This means that their effect compensated each other to a variable extent in different years for the pan-Mediterranean assessment.

Overall, these errors lead to a distortion and an overall underestimation of the actual loss of natural wetlands, which proved to be 30% higher than initially estimated (i.e. a natural wetland habitat loss of 13% instead of 10% in 30 years). The errors also caused an underestimation of the overall gain in human made wetlands which turned out to be +159% instead of the originally reported +54%. A re-analysis of the whole dataset had to be undertaken, using new internal decision rules of the Mediterranean Wetlands Observatory based upon the lessons learnt from the first, flawed analysis (e.g. Beltrame et al., 2015; MWO, 2014).

The steps followed can be viewed as a quality control for end products, i.e., both for maps and for key indicator values, such as the natural and artificial wetland surface at each date. This example of a posteriori quality control clearly demonstrates the need for wetland expertise and data to validate the remotely sensed produced maps.

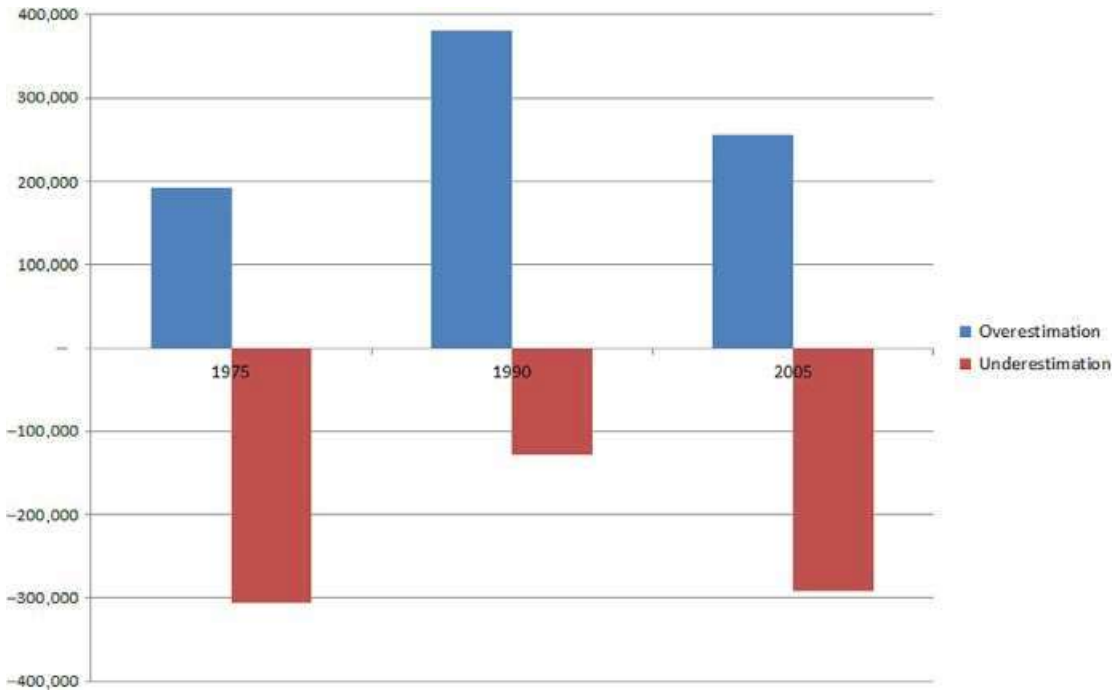


**Figure 6: Cumulated errors (in hectares) for the surface areas of natural wetland habitats for the 284 sites per studied period.**

A confusion (or error) matrix is an important requirement(e.g. Camilleri et al., 2017). It should be developed using ancillary data to quantify for each habitat class, or aggregation of classes, the risk of confusion withother classes and the overall error rate (both omission and commission). This will in turn allow any user to understand the limit of the end products and their margins of error, whether for decision making or for use in ecological modelling. Accepted error margins in wetland assessments at a single site are typically in the order of 10%-20% (E.G. Dadaser-Celik et al., 2008; Guo et al., 2017, Rapinelt et al., 2015).

In the GW-II project,the initially reported error rate across multiple sites was 12.4% for all habitat classes and 10.6% for wetland habitat classes (GlobWetland-II, 2014), although it later proved to be significantly higher. In two ongoing projects, SWOS (http://swosservice.eu/) and GlobWetland-Africa (http://globwetland-africa.org/), error margins of 15% are considered acceptable.

Similarly, when monitoring at wide geographical scales using standard RS-based approaches, results on status and trends (such as total areas of the different habitats at different dates) can also be checked for any unlikely and implausible changes. Wetland experts play a crucial role in detecting unlikely habitat changes which require a closer look. For instance, the transition of a freshwater lake into a coastal brackish lagoon, or transitions of thousands of hectares from lagoons into marshes are very unlikely over a 6-15 years period (see e.g. Ernoulet al., 2012). To increase the reliability of the errors rates produced by the validation protocol, when designing a ground-truthing validation protocol, wetland experts need to pay special care to identify what can or cannot actually be validated. Validation procedures for outputs (maps and trend indicators) are therefore most effective when they include both RS and wetland ecology expertise.

### 2.5 Concluding Remarks

The delineation and identification of Mediterranean wetland habitats can be tricky. RS specialists may not be able to grasp all the implications of how wetlands function and change over time. Ecologists and managers may also not understand the complexities and caveats (miss-classification errors) of creating remotely sensed maps of ephemeral wetland habitats. Technical development should therefore be coupled with ecological knowledge notably in deciding upon the required detail of nomenclatures, availability of ancillary data, accessibility to reliable information for the selection of training data (field information, ancillary data or local knowledge) and image frequencies, as well as development of explicit interpretation guidelines and validation procedures. An integrated approach can significantly improve the quality and accuracy of produced maps and indicators.

## 3. MAPPING THE WATER DYNAMICS OF WETLANDS

Beyond identifying wetland habitats, mapping flooded areas is essential, since wetland biodiversity reacts to flooding regimes, both in terms of quantity (flooded surfaces) and timing (hydrological cycles). The flood regime influences the distribution of aquatic plant species and communities aswellaswetlandprimaryproductivity(Dı´az-Delgadoetal., 2016; Tamisier and Grillas, 1994). The key elements for delineating and mapping flood extent and water dynamics using RS include ability to distinguish "inundated/flooded"vs"open/surfacewater"areas;goodseasonalcoverage of the whole hydroperiod; and a validation procedure involving groundtruth data and/or expertise on wetland ecology/hydrology.

### 3.1 Mapping Inundated or Open Water Areas

In this discussion,we define flooded (or inundated) areas as being covered by water irrespective of vegetation presence, and open (or surface) waters as flooded areas free of vegetation. This distinction is ecologically relevant, as key biodiversity features differ between these two zones. For instance, large flocks of wintering waterbirds will usually favour open waters, but not flooded areas with dense emergent vegetation (Tamisier and Dehorter, 1999). Yet, flooding regimes are important for the maintenance of emergent vegetation, which is typically used by waterfowl for nesting activities. As already discussed, imprecise terms may lead to ambiguous maps and/or interpretations (e.g. Aires et al., 2014). A more precise use of terminology would significantly increase the consistency and coherence between maps of flooding regimes.

Mapping flooded areas, especially under vegetation is a particular challenge. Although some long SAR wavelengths can penetrate vegetation (Hess et al., 2003), dense, emergent aquatic vegetation hinders the detection of water when using multispectral optical or radar sensors (Cazals et al., 2016; Horritt and Mason, 2001), in a variable way depending on the dominant species (Davranche et al., 2013). SAR sensors generally perform slightly better

although they do not penetrate the vegetation completely. As a consequence, “open water” areas which are easier to detect are often considered to represent “inundated/flooded areas” (e.g. Aires et al., 2014) causing the true extent of flooded areas to be underestimated (Fluet-Chouinard et al., 2015; Smith, 1997).

Currently, a combination of optical and SAR images offers the most reliable results (Toyr€ €a et al., 2002), and the Sentinel-1 and -2 developments are likely to make this approach feasible at larger and finer scales. Additionally, some tools using the mid-infrared band of SPOT-5 images have shown promising results for the mapping of surface water dynamics independently of vegetation type and density in shallow marshes (Davranche et al., 2013). A newly developed index, the Automated Water Extraction Index (AWEI; Feyisa et al., 2014) significantly increases the detection of surface water, by reducing the risk ofconfusion with other darksurfaces. Such accuracyproblems remained frequent until recently (Feyisa et al., 2014; Sanchez et al., 2015). The capacity of mapping water dynamics even under dense vegetation using Landsat-8 data was also improved by combining water indices like the Modified Normalized Difference Water Index (MNDWI: Xu, 2006) with vegetation indices like the Temperature Vegetation Dryness Index (TVDI: Gastal, 2016; Sandholt et al., 2002). However, in all cases, the use of ancillary data is strongly recommended to estimate mapping accuracy of flooded areas.

### 3.2 Images Covering the Whole Hydroperiod

Mapping the water dynamics of wetlands requires that the flood extent is mapped at different dates throughout the annual hydrological cycle (e.g. Camilleri et al., 2017). This information is often overlaid to produce a single map providing flooding duration of different wetlands according to classes, e.g., as “Never,” “Seasonally” and “Permanently flooded” areas (GlobWetland-II, 2011) over a given cycle, or as flood/submersion frequencies, i.e., percentages of the analysed images in which a given pixel was flooded (e.g. Davranche et al., 2013; Pekel et al., 2016; also see Fig. 7), or in terms of days/months (e.g. Dı´az-Delgado et al., 2016). Obviously, increasing the number of scenes will increase the precision of flooding duration estimation for highly seasonal wetlands. In the past, due to limited availability of cloud-free optical images, “water dynamics” maps have been produced with as little as two images from a hydrological year (GlobWetland-II, 2011), which is not sufficient for monitoring short-term dynamics of wetland hydrology having a seasonal water regime. SAR satellites provide an improvement for mapping open water dynamics throughout the year due to their independence of daylight and cloud cover. Furthermore, some sensors offer the ability to detect water overgrown by vegetation. Although several SAR satellite missions have been launched in the past decades, ERS, ENVISAT ASAR, TerraSAR-X and ALOS PALSAR to name a few, water body monitoring was hindered by infrequent data acquisition schemes and acquisition cost. General overviews on the use of SAR for wetland monitoring and water mapping are provided in Brisco (2015) and White et al. (2015).

A rather large and consistent historical image archive is available from the ASAR C-Band sensor aboard ESA’s ENVISAT satellite, which was operated from 2002 to 2012. In particular its Wide Swath Mode (WSM), although not optimal due to its limited VV polarization and low spatial resolution (150m), has been successfully used in several water mapping studies (e.g. Bartsch et al., 2008; Kuenzer et al., 2013; Matgenetal.,2011; Schlaffer et al., 2015)and also specifically to characterize wetlands by Schlaffer et al. (2016).

With ESA’sSentinel-1mission,currently consisting of two satellites with a combined repeatrate of down to 6 days and data provided at no cost, water dynamics mapping at high resolution and temporal frequency now becomes easier and cheaper. At the time of writing still only few publications can be found on Sentinel-1 water mapping, but it has been used for flood detection by, e.g., Boni et al. (2016) and Twele et al. (2016). Like ASAR WSM data, Sentinel-1 images are acquired in VV polarization. Thus, the imagery is very sensitive to waves, which can easily be mistaken for land surfaces (Brisco, 2015), as shown for instance in Fig. 7.

**Figure 7: Backscatter characteristics of water surfaces under different environmental conditions.Smooth water surfaces(left) appear as dark,while wind-induced waves generate a much brighter signal (right). The reduced contrast between water and land surfaces in the right image will result in large areas of water to be mistaken for land in automated classifications. Camargue, Southern France, Sentinel-1 IW VV, acquired on January 31, 2015 and February 05, 2015, respectively (approx. 50 Â 42km2). Produced from ESA remote sensing data.**

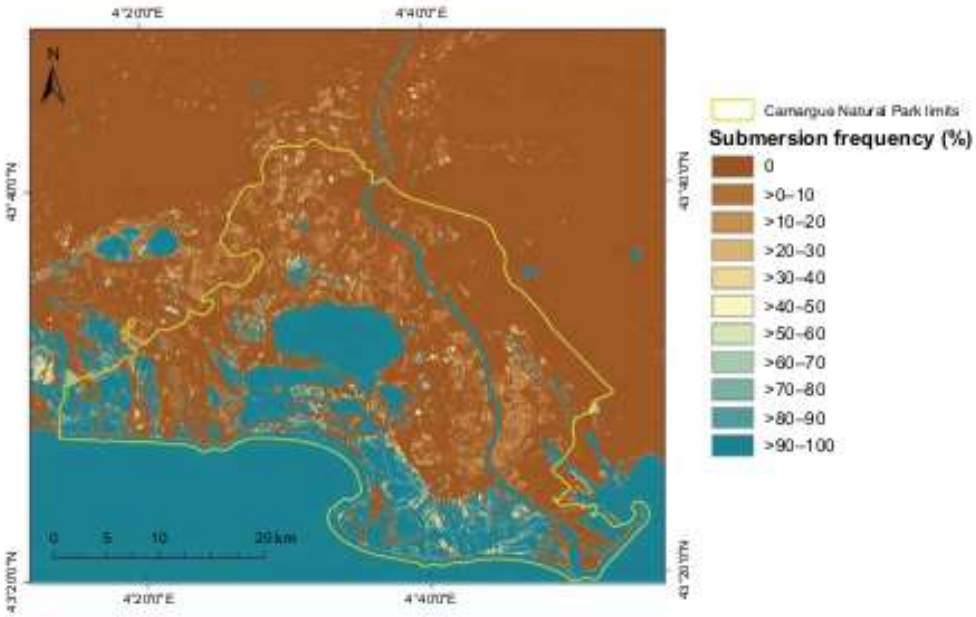


**Figure 8: Camargue, France: 2015 intraannual open water dynamics based on SAR data from Sentinel-1 Interferometric Wide Swath mode (IW). All available images acquired on 75 days throughout the year were included. Though an improvement from previous maps, some inconsistencies remain. Produced from ESA remote sensing data.**

One opportunity to circumvent this is by analysing the dense time series of images of individual pixels instead of the mostly used per image classification. For instance, Schlaffer et al. (2015, 2016) used harmonic models to estimate seasonal behaviour of SAR backscatter and detect outliers for flood detection. Fig. 8 shows an example of a time-series analysis technique, which assesses not only a pixel's intensity but also its class likeliness based on the temporal stability of the observed pixel. This way, images acquired under suboptimal conditions(e.g.heavy clouds or wind-induced waves) can be reliably classified, although the single scene shows no contrast between land and sea surfaces. This ongoing research will be extended to historic ASAR and ERS data once the approach has been refined to a satisfactory degree of accuracy. In the meantime, care has to be taken for trend analysis where flood regime maps are compared over time, notably for past trend analysis going back further than 1980.

### 3.3 Validation of Flood Regime Maps

Flood regime mapping has its own challenges and a thorough comparison with ground-truth data is required to validate final maps. Validation is less frequently performed for the flooding regime than for habitat classification, but Davranche et al. (2013) and Thomas et al. (015) found overall accuracy rates of 83% in the Camargue, France, and 93%-95% for the Macquarie marshes, Australia, respectively. A particularly robust field validation covering 6000 points in 31 ground-truth field campaigns from 2003 to 2013 was implemented in the Donana marshes, Spain, with an accuracy estimate of 94% (Diaz-Delgado et al., 2016).

A situation where careful validation is required is where hydrological cycles do not show regular annual patterns, e.g., in large temporary wetlands in arid regions which do not fill up completely every year, and whose outermost parts often remain dry. These margins should nevertheless not be identified as switching from dry (e.g. steppe) habitat to wetland habitat, depending on their seasonal or annual flood conditions (e.g. Fig. 9). To avoid these misclassifications which can lead to large errors in wetland area estimation, interpretation procedures may recommend to carefully reevaluate all rapid and unlikely back-and-forth shifts between dry land and wetland habitats.

### 3.4 Concluding Remarks

The hydroperiod is a crucial indicator for monitoring trends in ecology, functions and services of Mediterranean wetlands. Unfortunately, the mapping of flooding regime is also technically difficult.With increasing availability of multiple images per year, hydrological cycles as well as water extent under vegetation will potentially be better captured.However,for the interpretation of trends detected by RS, ecological knowledge is required to distinguish unpredictable variations typical of Mediterranean wetlands from actual habitat transitions.

## 4. DETECTION OF TRENDS OVER TIME

Opportunities and difficulties to identify habitat and flood extent of Mediterranean wetlands given the uncertainties in land cover maps and the irregularity of flooding regimes have been addressed in the two preceding sections. Use of RS observation to estimate long-term trends in ecosystem quality and biodiversity, infer some complementary challenges.

### 4.1 Uncertainty of Detecting Trends

A major question when it comes to detecting changes in Mediterranean wetlands is how to quantify the actual rates of change when they are in practice often inferior to, or of the same order as the error estimation. For instance, MWO(2014) detectedalossof10%innaturalwetlandsinasample of 214 sites between 1975 and 2005. However, the habitat classification error rate was estimated at 12.3% for any given year. In such cases, because the estimate falls within the confidence interval, a cautionary approach would be to refrain from estimating any quantitative loss; on the other hand, a qualitative systematic trend (e.g. an overall loss in wetland habitat) can still be tested rigorously, e.g., through nonparametric statistics applied to the large sample of sites. For a quantitative approach, the recent improvements in image resolution and frequency still need to be translated into lower error rates (i.e. narrower confidence intervals) for habitat mapping, so as to allow the detection of wetland habitat trends of, e.g., 5%-15%. Incertainty and error rates differ between habitat classes; for instance fewer errors are made when identifying sand and beaches than wet meadows. This means that the uncertainty of detected transformations of habitats depends on the habitat types involved, as reflected in the confusion matrices. Error rates for habitat identification are likely to decrease over time with the increasing availability of high-quality images, ancillary data and Mediterranean wetland expertise. To date, there is no estimation of the impact of the combined uncertainties on the detection of long-term trends (especially retrospectively) in Mediterranean wetlands, mainly due to a lack of validation data for older maps and this is unlikely to change.

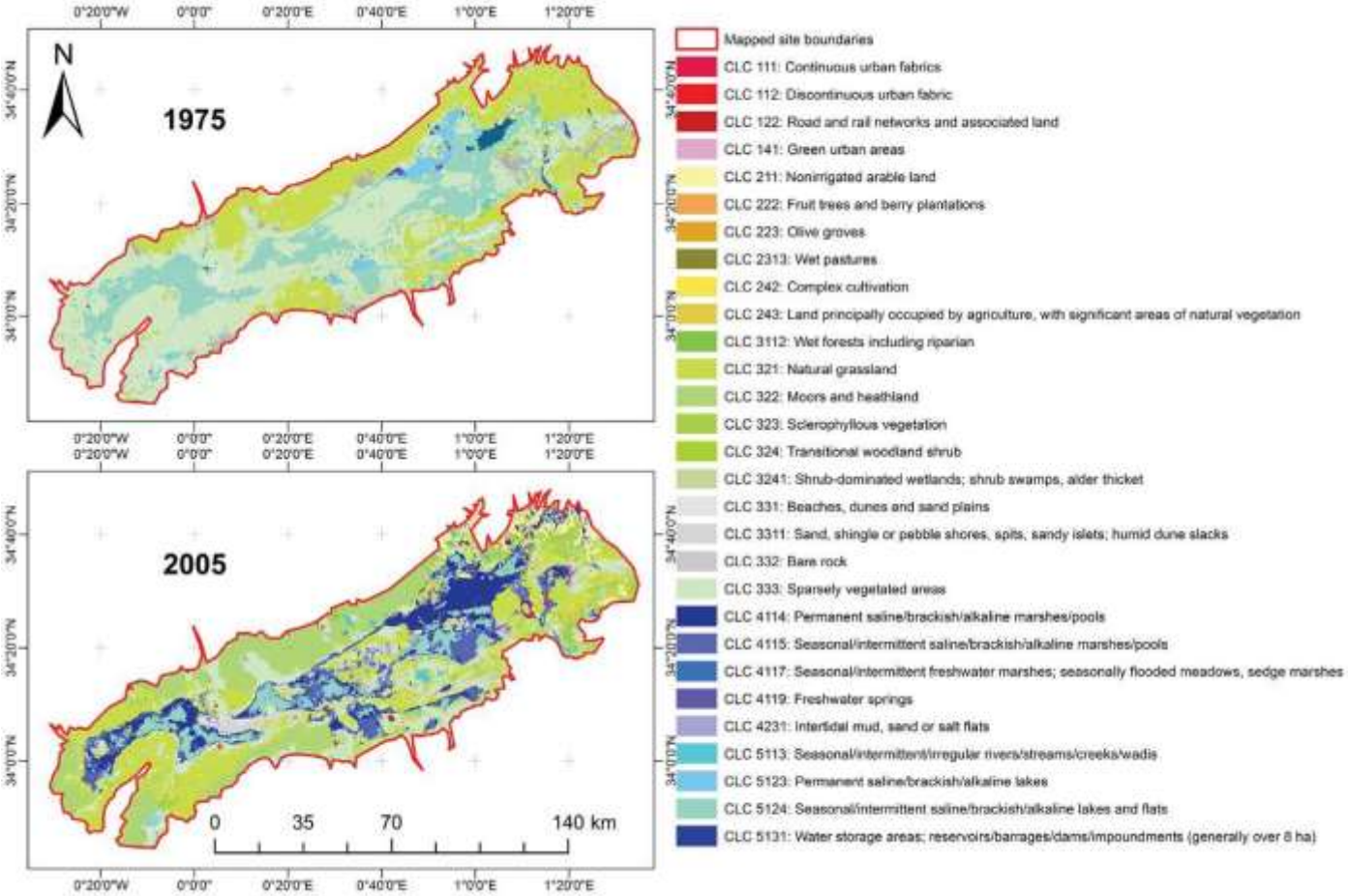


**Figure 9: A typical confusion affecting large wetlands in arid zones (Chott Ech-Chergui, Algeria) in 1975 (upper map) and 2005 (lower): a higher inundation level in 2005 due to higher rainfalls in previous years was mapped as "large increase in marshes, i.e. natural wetland area" (+147,000ha), and conversely as a "decrease in terrestrial habitats such as Steppes/Pastures." In reality the chott area did not vary; only its level of flooding did. At the pan-Mediterranean scale, this lead initially to underestimating the true natural wetland loss, since in the total figures for the 284 sites, this apparent "increase" offset 147,000ha of actual loss elsewhere (GlobWetland-II, 2014).**

## 4.2 Detecting Long-Term Changes When Flooding Extent Varies Interannually

Seasonal wetlands under dry climates (e.g. chotts and sebkhas) pose a particular challenge due to their extreme hydrological variability. Under such climates, rainfall is erratic and unpredictable, and so is the resulting extent of flooding in these typically large wetlands (see example of Chott Ech-Cherguy above fig. 9). Comparing two maps at a 15-20 interval may result, by chance alone, in comparing a very dry vs a relatively wet year—or the reverse—and a superficial analysis would conclude to a large increase (or conversely, decrease) in the flooding extent in a given site.

Detecting accurate long-term trends in wetland flooding remains an important issue, given the increasing human (e.g. MWO, 2012a) and climate (Giorgi and Lionello, 2008) pressure on freshwater in arid areas. One way to address this issue is to consider that trends in flooding regimes can only be assessed by using multiple seasonal maps over several years (e.g. the GSW produced by Pekel et al. (2016) and covering 32 years from 1984 to 2015). Although this approach is more time consuming, it will likely provide higher accuracy in trend estimations.

RS methods could also potentially borrow from ecological methods which aim to identify trends despite having very noisy data, e.g., occupancy or abundance modelling and other demographic modelling techniques.

### 4.3 Biodiversity: Changes in Ecosystem Quality

Tracking changes in wetland types and extent is important but distilling indications on ecosystem quality bring us closer to the monitoring of trends in biodiversity. Here we zoom into efforts on identifying habitat fragmentation, time lags in responses of Mediterranean biodiversity to water shortage and measures of water quality.

Many studies and projects have developed habitat fragmentation indices (e.g. Liu et al., 2014; Tomaselli et al., 2012), most of which are based on the assumption that a reduction in (natural) habitat extent should be interpreted as an increase of habitat fragmentation. Some of these indices are based on the evaluation of the landscape connectivity using specific metrics related to the size of habitat patches and the distance between them (Minor and Urban, 2008). However in the case of Mediterranean wetlands characterized by temporary water coverage, the variability in intra and interannual surface water is not necessarily linked to these fragmentation metrics. For instance, temporary ponds may be connected during times of high water availability and separated in periods of water shortages—without any implication in terms of habitat fragmentation. This dynamic is natural for Mediterranean wetlands and occurs with a frequency which is not always predictable. The detection of trends in habitat fragmentation therefore has to take into account the ecological reality of what defines a temporary wetland habitat in the Mediterranean region (Perennou et al., 2013). Assessing long-term trends in wetland fragmentation will therefore require data series analysed over a long period to distinguish natural variability in habitat delineation from a long-term degradation of habitat extent. This should be used carefully, and only when long time series of data are available.

Long-term data series are also required for predicting the impacts of changes in flooding regimes on Mediterranean biodiversity. Many taxa and species are adapted to unpredictable availability of water and long periods of water shortages. For instance, the flamingo Phoenicopterus ruber is a long-lived species with an optional nesting behaviour adapted to fluctuating conditions; the mosquito Ochlerotatus caspius lays quiescent eggs on the ground which can survive to long periods of drought (Balenghien et al., 2010); damselflies found in brackish temporary marshes in the Camargue exhibit strong interannual variations in abundance related to marsh flooding duration (Aguesse, 1961); abundance of breeding passerines in temporary reedbeds depends on the duration of flooding from June through December in the preceding year, which determines food level during the following nesting season (Poulin et al., 2002). This means that the impact of one dry spell on overall species richness and abundances is hard to predict, and that species richness and abundances may react with a time lag relative to long-term trends in water shortages: longer time series are therefore required.

A key component of ecosystem quality is water quality. It is a long-term driver for biodiversity in Mediterranean wetlands, especially because nutrient runoff and pesticides from agriculture, as well as wastewater from settlements often end up in wetland habitats (EEA, 2012). Beyond pollutants, other substances like suspended particulate materials (SPMs) originating from soil erosion can affect biodiversity. Eutrophic (nutrient-rich) waters are usually characterized by a high productivity and a poor plant and animal species richness. Nutrients cannot be directly estimated by RS, but high nutrient availability often leads to massive development of algae. Since the concentration of chlorophyll a, the main pigment in algae, can be estimated from RS data (e.g. Brezonik et al., 2005; Matthews, 2011; Odermatt et al., 2012; Ritchie et al., 2003), it often serves as an index for algal biomass and as a proxy for eutrophication.

Turbidity is another common water quality parameter that can be estimated from RS data (Dogliottietal.,2015; Ritchieetal.,2003). Turbidity is related to the concentration of SPM. At this moment, it is not possible to separate artificial from natural turbidity based on RS data alone. The suspended particles will affect the transparency of the water and therefore the transmittance of sunlight through the water, which can result in low plant productivity. In addition, the dissolved organic matter (DOM) present in natural waters is known to absorb light and therefore also affects water transparency. The coloured fraction of the dissolved organic matter (CDOM) is an optically active substance that affects the reflectance measured by the satellite sensor, and which thereby can be estimated based on RS data (Beltran-Abaunza et al., 2014). These substances bind metals as well as organic contaminants, and

organic substances from discharges are one major cause of pollution in surface waters, which can have a strong effect on biodiversity.

Especially adapted high-frequency images do exist for estimating water quality parameters (e.g. MERIS and Sentinel-3), but the spatial resolution is only300m,which limits the applicability to larger water bodies.Inaddition, a proper estimation of the water quality requires that the water is optically deep, i.e., that the bottom substrate cannot be seen from the surface. Many shallow wetlands are not of sufficient depth for RS to provide useful information and indicators on these issues. Improvements are expected from new images of high spatial resolution provided by Sentinel-2A (launched in 2015) and 2B (launched in 2017), which should enhance our capability to monitor water quality from space in smaller water bodies. Sentinel-2 applications are especially relevant for small lakes and for patchy waters where few or no information exists. In these habitats, Sentinel-2 can contribute to a first assessment of the water condition, in terms of eutrophication, transport of suspended sediments and distribution of invasive floating plants such as the water hyacinth Eichhornia crassipes.

### 4.4 Concluding Remarks

The ultimate objective of detecting and quantifying trends in Mediterranean wetlands and their biodiversity over time is a challenge that largely remains unsolved. New Sentinel-3 data could provide promising advances and potential on estimates of water quality. More work is needed to address how we can relate computations of flood regimes to changes in quality of ecosystems and their related species richness and abundances.

## 5. CONCLUSIONS

The use of RS data for the mapping and monitoring of wetlands of arid and semi arid areas such as the Mediterranean has improved since 1980. To allow for the progress made to be included in the RStools and interpretation procedures that are being developed for new types of RS data, we here summarize the most important progress made in the form of recommendations, as well as the challenges that still need to be addressed. By identifying current best methods as well as gaps, this chapter contributes to the development of a repository for best practices of wetland RS under the framework of GEO Wetlands, and to applications beyond the Mediterranean ecoregion.

In general, the uncertainties that come with any method applied to RS data can be greatly reduced by integrating ecological expertise and ground truth data in the different steps of the technical process. This chapter uses several ways to do this. To increase accuracy of RS products, ecological understanding of the habitats and their dynamics is required. This can be achieved by developing RS products through active collaboration with ecologists and site managers. This would allow RS experts to improve monitoring tools and ecology experts to recognize both the value and the limitations of RS data, as recommended by Skidmore et al. (2015).

The development of a robust habitat nomenclature for Mediterranean wetlands that would fulfil the needs of scientists, managers and decision makers is a tricky task, especially for an application to areas where we can only rely on RS data for monitoring these habitats. Habitat maps using typologies with many classes require enhanced validation procedures with ancillary data or expert knowledge. To ensure low uncertainties in largescale mapping exercises, the number of habitat classes can be reduced, but this also means that some of the changes, i.e., those occurring within one of the enlarged habitat classes, will go undetected. In addition, if the purpose of a map is to inform management decisions, a more detailed classification may be required.

Uncertainties can be further reduced and consistency across maps increased, through the development of protocols for habitat identification based on integrated knowledge of wetland ecology and hydrology and RS techniques. In particular, interpretation protocols which stipulate explicit decision rules for habitat identification as well as rigorous validation procedures, can both help reduce and quantify the error estimates for each habitat class. Any mapping activity should be complemented by a systematic validation phase that should be developed and

continuously adapted to include unlikely habitat transformations, recurrent interpretation errors, risks of confusion between habitats and flood extent, and focused efforts on difficult clusters of habitats.

To date, a number of challenges have been solved at the local scale of one site through the use of local experts or available ancillary data, and for assessing one-off, recent situations through improved satellite imagery. However, that does not solve the double challenge for larger-scale assessments or multisite assessments (e.g. the Mediterranean region), and for retroactive studies, i.e., comparisons with the earlier periods of RS. Progress is still needed to better segregate particular habitats, such as wetmeadows from other meadows, lagoons and lakes from their peripheral marshes, and ricefields from other crops. Estimates of changes in Mediterranean wetland biodiversity would be greatly improved if we could better separate similarlooking natural vs man-made habitats, e.g., lakes vs reservoirs or fish ponds, or lagoons vs salinas. Citizen science could be used for these, for instance by getting people to send their photos, or using online georeferenced photos to confirm classifications. Changes in the flood regimes of Mediterranean wetlands still requiresbetter detection of flooding under dense and/or emergent vegetation, as well as the development of procedures for distinguishing the natural variability in hydrological cycles from long-term trends. And, last but not least, the ability to develop reliable tools for monitoring long-term trends in wetlands of arid and semiarid areas such as the Mediterranean will require the quantification of uncertainties, both for individual maps and for changes derived from comparison of maps over time.

## ACKNOWLEDGEMENTS

This work was partly supported by a suite of completed and ongoing projects, namely GlobWetland2 (GW-II), GlobWetland-Africa, SWOS and ECOPOTENTIAL. GW-II was a European Space Agency (ESA-DUE) project, in partnership with the Ramsar Convention on Wetlands and the Mediterranean Wetlands Observatory. GlobWetland Africa is an Earth Observation application project funded by the European Space Agency (ESA) in partnership with the African Team of the Ramsar convention. SWOS (Contract No. 642088) and ECOPOTENTIAL (Contract No. 641762) are ongoing projects under the Horizon 2020 Programme funded by the European Commission. SWOS and GlobWetland Africa are partners to the GEO-Wetlands Initiative, to which this study contributes. The authors are grateful to the Editor and two anonymous reviewers for suggesting substantial improvements.

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