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ECOSYSTEMS BASED ON REMOTE SENSING TIME SERIES

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Abstract

RESUMEN

Hay una creciente preocupación a nivel global por la conservación de los recursos hídricos. Los ecosistemas de arroz, responsables del consumo del 30% de los recursos hídricos utilizados en agricultura (Karaba et al., 2007) son un elemento clave para asegurar la disponibilidad de agua. Además, los arrozales poseen una importante biodiversidad acuática y terrestre, y producen un alimento básico a nivel mundial, siendo el elemento más importante en la dieta de la mitad de la población (Van Nguyen & Ferrero, 2006). En un contexto de creciente demanda de arroz y escasez de agua (Bouman et al., 2007), con serias implicaciones en la disponibilidad de recursos hídricos y en la conservación medioambiental, la obtención de información sobre el uso del agua en los ecosistemas de arroz es una necesidad crucial. Sin embargo, el suministro de información fiable y actualizada sobre la distribución y los cambios en las zonas de arroz (Dong et al., 2015), así como la provisión de métodos precisos de detección de inundaciones y fenología a nivel global siguen presentando dificultades. Además, mejorar la estimación de la evapotranspiración (ET) y sus variaciones temporales y espaciales es esencial para mejorar la planificación de la gestión del agua (Lee et al., 2004, Chemin y Honda, 2006).

La teledetección se ha convertido en una herramienta clave para el seguimiento, elaboración de mapas y observación de los ecosistemas de arroz en diferentes escalas temporales y espaciales (Kuenzer & Knauer, 2013), proporcionando información fiable de manera instantánea y costo-efectiva. El análisis de series temporales de datos de teledetección proporciona información importante para evaluar la dinámica de los ecosistemas (Zhang et al., 2003). Además, el uso de series temporales de índices espectrales constituye un método sólido para identificar dinámicas intraanuales e interanuales, y se ha aplicado en estudios sobre el uso del suelo, detección de sucesos fenológicos y el seguimiento de los fenómenos naturales, entre otros (Gumma et al., 2014, Shijua y otros, 2014, Simonneaux et al., 2008).

En la presente Tesis se propone una metodología para el seguimiento de la dinámica del agua y la vegetación en ecosistemas de arroz a partir de series temporales de índices espectrales y el uso de series temporales de teledetección en combinación con modelos de ET. Las metodologías que se han estudiado están pensadas para ser aplicadas con bajos requerimientos de datos de campo, con el objetivo de que sean factibles en regiones que carecen de información agrícola general, y especialmente en los países en desarrollo. Se han utilizado las series temporales MODIS para obtener resultados con suficiente frecuencia temporal y poder contar con bandas espectrales adecuadas para detectar fenómenos de agua y vegetación. Los objetivos específicos fueron (1) explorar la potencialidad de las series temporales anuales de los índices espectrales para cartografiar los ecosistemas de arroz; (2) evaluar el potencial de diferentes índices espectrales para el seguimiento de la fenología del arroz y la dinámica de la inundación combinando enfoques fenométricos y estadísticos de series temporales y (3) evaluar el funcionamiento del modelo Priestley Taylor-Jet Propulsion laboratory (PT-JPL) diario para obtener λE (ET expresado en términos de Energía) en los ecosistemas de arroz.

Los resultados de esta Tesis confirmaron el potencial de los índices de vegetación para proporcionar mapas fiables de arroz y resaltaron la importancia de explorar los índices angulares para mejorar la identificación de la dinámica de la cubierta terrestre. En particular, el uso del Índice de Ángulos y Pendiente Espectral (SASI) ha demostrado su potencial para proporcionar resultados

notables en la discriminación del arroz de otros cultivos o usos de la tierra, en combinación con técnicas de emparejamiento espectral. La existencia de una respuesta significativa a los eventos de inundación mostrados en los Índices de Agua de Diferencia Normalizada (NDWI (1), NDWI (2)) y SASI ilustra la importancia de las longitudes de onda espectrales infrarrojas de onda corta (SWIR) para detectar suelos inundados y húmedos. Específicamente, el SASI mostró una gran capacidad para identificar cambios en el contenido de agua en el suelo, lo que podría fomentar su uso en estudios de seguimiento de humedales. Sobre la base de los resultados obtenidos, hemos propuesto una combinación específica de índices para evaluar los eventos de inundación del arroz y las etapas fenológicas en relación con diferentes prácticas de gestión. El modelo PT-JPL-diario reprodujo adecuadamente la dinámica principal de λE en los ecosistemas arroceros durante la época de crecimiento del arroz, pero fue menos fiable en la reproducción de los valores variables presentes fuera de este período.

ABSTRACT

Water resources conservation is becoming an increasing concern worldwide. Rice ecosystems, as the consumer of 30% of freshwater resources used for crops worldwide (Karaba et al., 2007) are a key element to ensure water availability. Besides, rice fields hold important aquatic and terrestrial biodiversity, and produce crucial staple food at global level, being the most important element in the diet of half of the world's population (Van Nguyen & Ferrero, 2006). In a context of increasing rice demand and water scarcity (Bouman et al., 2007), with serious implications in water resources availability and environmental conservation, obtaining information about water use in rice ecosystems is becoming a crucial need. However, the provision of reliable and updated information on rice paddy distribution and changes (Dong et al., 2015), as well the provision of accurate flooding and phenology detection methods is still difficult at global level. Furthermore, improving the estimation of evapotranspiration (ET) and its temporal and spatial variations is essential to improve water management planning (Lee et al., 2004; Chemin and Honda, 2006).

Remote sensing has become a key tool to monitor, map and observe rice ecosystems at different time and spatial scales (Kuenzer & Knauer, 2013), providing reliable information in an instantaneous and cost-effective manner. Time-series analysis of remote sensing data provides important information to assess ecosystem dynamics (Zhang et al., 2003). Additionally, the use of spectral indices time series is also a solid approach to identify intra-annual and interannual dynamics, and has been applied in the fields of land-use identification, phenology detection and natural phenomena monitoring, among others (Gumma et al., 2014; Shihua et al., 2014; Simonneaux et al., 2008).

In the present thesis, a methodology is proposed to monitoring water and vegetation dynamics in rice ecosystems based on spectral indices time series, and the use of remote sensing time series in combination with ET models. The options explored are intended to be applied with low field-data requirements and inputs, aimed to be feasible in regions lacking general agricultural information, and especially in developing countries. We used MODIS time series to achieve results with enough time frequency and adequate spectral bands to detect both water and vegetation phenomena. The specific objectives were (1) to explore the potentiality of Spectral Indices annual time series to map rice ecosystems; (2) to assess the potential of different spectral indices for monitoring rice phenology and flooding dynamics by combining phenometric and statistical time series approaches and (3) to evaluate the Priestley Taylor- Jet Propulsion laboratory (PT-JPL) daily model performance in obtaining λE (ET, expressed in terms of energy) estimates in rice ecosystems.

The results of this thesis confirmed the potential of vegetation indices to provide reliable rice maps and highlight the importance of exploring angular indices to improve the identification of land cover dynamics. In particular, the use of the Shortwave Angle Slope Index (SASI) has demonstrated its potential to provide remarkable results in discriminating rice from other crops or land uses, in combination with spectral matching techniques. The existence of a significant response to flooding events showed in the Normalized Difference Water Index (NDWI(1), NDWI(2)) and SASI illustrates the importance of SWIR spectral wavelengths to detect flooded and wet soils. Specifically, SASI exhibited a strong capacity to identify changes in soil water

content, which may encourage its use in wetland monitoring studies. Based on the results obtained, we have proposed a specific combination of indices for assessing rice flooding events and phenological stages in relation to different management practices. The PT-JPL-daily model reproduced adequately the main dynamics of λE in rice ecosystems during the rice growing season, but it was less reliable in reproducing the repeated ups and downs present out of this period.

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CHAPTER 1

Introduction

Chapter 1. Introduction

1.1 Rice fields as wetland ecosystems. Importance of rice ecosystems at global level.

Wetlands cover 6% of the world's land surface (Erwin, 2009). In these ecosystems the soil is covered by a water layer or presents a shallow water table, all year or irregularly during the year. According to the Ramsar Convention, wetlands are 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. They provide valuable ecosystem services, such as biodiversity conservation, water quality improvement and flood abatement (Zedler & Kercher, 2005). Rice fields can be considered as seasonal wetland ecosystems agronomically managed (Bambaradeniya et al., 2004), and they are considered in this form under the Ramsar Convention, representing 15% of the world's wetlands today (Lawler 2001). Rice paddy ecosystems occupy 163 million ha and approximately 12% of global cropland area worldwide (FAOSTAT, 2010 and 2014), being the main source of cereal crops in developing countries (Juliano, 1993). There are 111 rice-growing countries in the world. In the European Union, rice is cultivated in about 400.000 ha, mostly in Mediterranean countries: Italy (49%), Spain (29.7%), Greece (6.7%) and France (4.5%) (Manfron et al., 2012).

Rice ecosystems hold important aquatic and terrestrial biodiversity. Unique species of invertebrates, vertebrates and flora, crucial for both agroecology and conservation biology, are dependent of them (Bambaradeniya et al., 2004). Particularly, some studies have indicated that rice fields can provide suitable habitat for water birds in comparison with seminatural wetlands (Elphick, 2000), highlighting the importance of water management practices in biodiversity conservation (Lourenço, and Piersma, 2009). Additionally, rice paddies have been recognized as valuable ecosystems providing a wide variety of ecosystems services such as flood control, groundwater recharge, water supply and water purification, air purification and cooling, and social benefits, sometimes more important economically than rice production itself (Whashitani et al., 2007; Yoon et al., 2009). Thus, water management in rice fields have strong implications for biodiversity conservation and ecosystem services provision.

Besides, rice is a crucial staple food at global level, being the most important element in the diet of half of the world's population (Van Nguyen & Ferrero, 2006). In a context of increasing world's population, estimated to reach 8.27 billion in 2030, rice demand is projected to rise from 571.9 M tonnes in 2001 to 771.1 M tonnes in 2030 (Van Nguyen & Ferrero, 2006). Meeting this demand will have serious implications in land use, water resources availability and environmental conservation. These effects would be especially relevant in developing countries expecting to increase their rice production, and particularly in Africa, where rice has become critical for food security and political stability (Center, 2011). Additionally, in many Mediterranean rice ecosystems, water availability is restricted due to the existing competition for limited water resources, and this situation will deteriorate in the context of climate change scenarios for the region (Moreno-Jiménez et al., 2014).

1.2 Rice ecosystem features and cycle.

Rice is usually grown as an annual monoculture. However, the rice ecosystem flora include rice plants (*Oryza sativa* or *Oryza glaberrima*), but also many types of microalgae and other vascular macrophyte. The plant has slender leaves and flowers in panicle that turn yellow when the rice in the panicle ripens.

Fig.1.1. Flooded rice field in September in the Ebro Delta (Spain)

In most places, rice is cultivated in flooded conditions, presenting clear seasonal dynamics marked by soil flooding, soil drainage and plant growing. Rice is extremely affected by water shortage. The lack of soil water content below saturation levels reduces growth and yield formation, implying decreased leaf surface area and a reduction in the photosynthesis rate (Bouman and Tuong, 2001). Traditionally, rice is grown in a single cycle per year, being the most common practice in temperate zones. However, double-cycle rice is not unusual, especially in tropical zones in Asia. According to the International Rice Research Institute (IRRI, 1993), rice land ecosystems can be classified into four categories based on their hydrological conditions: irrigated rice ecosystem, rainfed lowland rice ecosystem, upland rice ecosystem, and flood-prone rice ecosystem. All these systems, apart from the upland system, are based in wet cultivation methods. About 75% of rice is grown in irrigated systems, while rainfed rice is grown in one quarters of the world's rice lands (Halwart & Gupta, 2004).

Rice cycle lasts between 120-140 days, depending on varieties and climate conditions (Kuenzer & Knauer 2013). It may be established by direct seeding or by transplanting, once the land is fully flooded. Rice growth can be classified into three phases. In the vegetative stage (1), the vegetative part grows, and the green canopy progressively covers all the water surface until reaching the heading date. On that point, the maximum biomass levels in rice occurs, and the vegetative growth stops. After this point the reproductive stage (2) takes place and the inflorescence develops and flowers. Finally, in the ripening stage (3) the grain matures turning yellow, while the vegetative part keeps its green colour until harvest.

Fig. 1.2 Rice growth stages. IRRI, 2014.

1.3 Water management and monitoring in rice ecosystems.

Water resources conservation is becoming an increasing concern worldwide. Irrigated agriculture, due to its intense use of available water resources, is a key element to ensure water availability. The Water Framework Directive 2000/60 / EC establishes the need to study all human activities that may have an impact on the status of surface water bodies, including those derived from water management in irrigated agriculture. Additionally, total crop water needs are projected to increase to 12,050–13,500 km³ by 2050 (Viala et al., 2008). In this sense, a careful irrigation and drainage water management is essential to improve the quantity and quality of water available for other uses (FAO, 2002.a).

Conventional water management in rice paddies involves keeping the fields permanently flooded, being the consumer of 30% of freshwater resources used for crops worldwide (Karaba et al., 2007). Rice irrigation requires more water than actually utilized by the crop (Bouman et al., 2007), in order to keep flooding conditions in the rice field. The aquatic environment in rice fields is normally shallow, with variations in turbidity. It presents strong variations in water temperature, with diurnal fluctuations that are often about 5°C, decreasing with increased density of the rice canopy (Halwart & Gupta, 2004). The water level is usually maintained between 2.5 -15 cm, depending on water management practices and rice varieties. In temperate zones, rice paddies are flooded at the end of April. The water in the fields commonly flows continuously, from the entrance to the drain, which leads the water through the drainage network of the rice area for their disposal. In saline soils, typical in deltas and coastal rice fields, flooding is essential for controlling soil salinity levels in the root zone. During the rice growing stage, the water level may be reduced periodically to promote seedling establishment or to allow the application of herbicide or fertilizers. Water level are also typically lowered or even completely drained around 10 days before the harvest. After harvesting, the fields are usually drained and kept dry until the next rice cycle.

However, there are some practices in rice fields that implies additional flooding practices after the harvest. Traditionally, water management in rice paddies implied some degree of water retention in the fields during the winter (Wood et al., 2011), especially in Asia. Nowadays, these practices

are becoming important again in different zones of Japan, Spain or USA (Kurechi, 2007; Washitani, 2007) in relation with biodiversity and soil conservation. Environmental flooding practices allows rice fields to function as wetland habitat for preserving biodiversity in those zones. This practice consist of continuous wetting of paddies during winter when rice plants are not growing, in combination with reduced or non-existent chemical applications during the rice cycle. Additionally, the flooding of rice fields out of the rice season is common in rice-fish systems, a farming method combining rice cultivation and aquiculture practices typical in many parts of Asia (Wood et al., 2011; Natuhara, 2013). Although these practices have been in decline, particularly in Japan and China, they are now being reconsidered (Natuhara, 2013) due to their proved mutual benefits for rice and fish production and the decrease in the need for pesticides (Halwart & Gupta, 2004; Wood et al., 2011).

In a context of increasing rice demand and water scarcity (Bouman et al., 2007), providing information about water use in rice ecosystems is becoming a crucial need. However, addressing water monitoring in relation with rice paddies presents many challenges at global level. The provision of reliable and updated information on rice paddy distribution and changes (Dong e al., 2015), as well the provision of accurate flooding and phenology detection methods is still difficult. Additionally, a sound estimation of the water balance in rice ecosystems depends on the correct accounting of water inputs (irrigation, rain) and outputs (evapotranspiration (ET), drainage), being ET one of the most challenging hydrological flux to estimate, especially at regional or global scale (Liou & Kar, 2014). Thus, improving the estimation of ET and its temporal and spatial variations will be essential to improve water management planning (Lee et al., 2004; Chemin and Honda, 2006).

1.4 Rice ecosystem mapping and monitoring based on remote sensing data.

Monitoring and mapping rice ecosystems in a timely and efficient manner throughout space and time is key to develop more sustainable farming systems, reducing environmental impacts while responding the continuous increment in food demand (Xiao et al. 2006). This issue is particularly important in developing countries, where the need of improving information systems on the rice sector was detected as a result of the rice crisis in 2008 (Center, 2011). Remote sensing has become a key tool to monitor, map and observe rice ecosystems at different time and spatial scales (Kuenzer & Knauer, 2013), providing reliable information in an instantaneous and cost-effective manner.

Rice ecosystems are complex, dynamic and highly diverse, and therefore they present a challenge for remote sensing techniques. Rice plants presents the typical signature of herbaceous plants, with low reflectance in the visible part of the spectra and high in the near infrared region, 700-1300 nm (Ustin, 2004). As the rice grows and develop, two components evolve affecting the signal received by the sensor: soil signals, including water content, and plant signals, due to changes in the hemispherical leaf reflectance and tramitance, and changes in the geometry of the canopy (Ustin, 2004). Underlying water and soil surface dominates the reflectance signal during the first weeks after transplanting or seedling (Kuenzer & Knauer, 2013), or during winter flooding period, if present. During the vegetative stage, reflectance in the near-infrared (NIR) region is dominant. Red reflectance diminishes from 10% at emergence to 2% at flowering and then increases to 16–

18% at maturity due to loss in green brightness by the leaves and stems plus the yellowness of the rice grains (Casanova et al., 1998). In most cases, the spectra of rice are influenced by the water regime and flooding conditions (Kuenzer & Knauer, 2013).

Remote sensing techniques have proved to be useful in different aspects in relation with rice ecosystems: mapping rice-growing areas; assessment of rice growth and health status; ecosystem evaluation and assessment of environmental impacts, such as land degradation and soil salinity; hydrologic assessment and monitoring, such as water use assessment and flooding monitoring; and estimation of climate change relevant emissions, among others (Kuenzer & Knauer, 2013). Each application has specific requirements that have to be met by a suitable sensor, in terms of spectral, spatial and temporal resolution.

MODIS sensor, aboard the Terra and Aqua satellites is potentially an optimal tool to provide long-term information of inter-annual and intra-annual dynamics in rice ecosystems. MODIS produces freely-available views of the entire Earth's surface every 1-2 days at spatial resolutions of 250, 500 and 1000 m. Some of their 36 spectral bands are specific for vegetation and water detection (Xiao et al., 2005), and particularly, reflectance at 1230 nm (SWIR1), rarely present in other sensors, has proved to be a key observation for agricultural studies (Palacios-Orueta et al., 2012). Both the MODIS spectral resolution and high frequency constitute critical requirements for rice systems analysis (Peng et al., 2011; Dong & Xiao, 2016). It also includes advantageous features such as a thermal infrared band to detect air temperature and humidity, crucial in addressing ET estimation. Additionally, MODIS provides several products, such as albedo product, Leaf Area Index (LAI) and the fraction of absorbed photosynthetically active radiation (f_{APAR}), useful in hydrological modelling and vegetation productivity assessment (Fensholt et al., 2004), and particularly in some ET models.

1.5 Potential of spectral indices in relation with rice ecosystem monitoring.

Remote sensing data from multispectral sensors is usually summarized in spectral indices (Huete et al., 2002), combining the information contained in different spectral bands. Their use present several advantages: ease of use, potential to measure known functional or structural properties and the decrease of the influence of external factors, such as background and atmosphere, among others (Palacios-Orueta et al., 2012). In relation to rice ecosystems, spectral indices sensitive to water, soil and vegetation are necessary for monitoring changes in the mixture of surface water, bare soil and green vegetation in paddy rice fields (Sari et al., 2010). The Normalized Difference Vegetation Index (NDVI), based in the Red and NIR bands, is sensitive to photosynthetic activity and vegetation dynamics. It allows comparisons between seasonal and interannual changes in vegetation growth and activity (Cheng & Wu, 2011), and has been widely used in rice studies (Boschetti et al., 2009; Wang et al., 2012; Gumma et al., 2014). The NDVI also shows some sensitivity to soil wetness, being suitable for monitoring irrigation start and padding (Motohka et al., 2009). An alternative way to detect vegetation and water dynamics is the use of indices based on the infrared spectral range (1240–3000 nm), which include SWIR1 and SWIR2 bands. This is considered the most suitable spectral domain for identifying these dynamics due to the presence of specific physical water absorption features (Boschetti et al., 2014). The Normalized Difference Water Index (NDWI(1)), combining information from NIR and SWIR1 bands, is sensitive to soil

and vegetation water responses (Gao, 1996) and thus, it is potentially useful to detect soil dynamics in rice fields. Additionally, NDWI(2), which combines SWIR2 and NIR bands, has also demonstrated potential to identify vegetation liquid water (Xiao et al. 2002), and has received comparatively little attention in rice studies. However, it is still difficult to detect accurately ecosystems dynamics when photosynthesis is not the dominant process (Palacios-Orueta et al., 2012). Particularly, detecting the transitional phases from wet to dry soil, and from wilting vegetation to bare soil is still challenging. In this sense, there is a need to study new indices to provide a more realistic indication of moisture in vegetation and soil in rice paddies (Das et al, 2014).

The Spectral Shape Indices (SSI), which parameterize the general shape of the spectrum by measuring the angle formed by three consecutive MODIS bands (NIR, SWIR1 and SWIR2), were first conceptualized by Palacios-Orueta et al. (2006) and represent a new paradigm in the use of vegetation indices. The use of SSI has demonstrated promising results in crop and rainfall monitoring, (Palacios-Orueta et al., 2006; 2012) and has potential to outperform other indices in identifying complex ecosystem dynamics, such as those in rice ecosystems. Based on this work, Khanna et al., (2007) developed the Shortwave Angle Slope Index (SASI), which showed special features to discriminate among dry soil, wet soil, dry vegetation and green vegetation. This index has already been studied for its unique response to surface moisture changes, and has showed excellent results in tracking surface wetness and rice transplantation pattern (Murthy et al., 2012), and in determining soil dryness and wetness in crops through threshold values (Das et al., 2013). Accordingly, the assessment of SASI potential to reproduce rice ecosystem dynamics may provide meaningful results, especially in relation with changes in phases between dry soil, wet soil and green vegetation.

1.6 Use of remote sensing data to assess ET in rice fields.

Evapotranspiration (ET) accounts for the evaporation and transpiration of water vapor occurring simultaneously in vegetated areas, being difficult to measure them separately.

In rice fields, water is lost mainly by evaporation during the winter flooding and during the first stages of the rice cycle. As the rice grows, the transpiration becomes more relevant. Due to this complexity of surfaces and covers, flooded ecosystems remain as challenging environments to estimate ET (Drexler et al., 2004). There are several available methods to estimate ET, with substantial differences in their need of parameters (Lee et al., 2004) and their capacity to provide estimates at large spatial and temporal scales. Additionally, data availability is an important constraint to consider in ET calculation, but especially in developing countries. Therefore, many efforts have been made to develop specific techniques to estimate ET in zones lacking specific data (Lee et al., 2004). In line with this, the use of remote sensing time series as the input data in ET models is particularly advantageous, producing estimates at large spatial and temporal scales.

Energy is required to evaporate water, and accordingly, solar radiation and air temperature are key parameters in relation with ET (FAO, 1998). Therefore, ET can be expressed in terms of energy balance as latent heat flux (λE). The approaches to calculate λE based on surface energy balance and remote sensing data, and specifically two sources-models, have become increasingly recognized (Yao et al., 2010; Wang & Yamanaka, 2014). These models compute canopy and soil

heat fluxes separately, being robust for a wide range of landscape and hydrometeorological conditions (Kustas et al. 1996; Zhan et al. 1996; Kustas and Norman 1997). However, λE estimation in flooded ecosystems, such as rice fields, present many difficulties: intra-annual variations in surface cover, air advection and the quantification of water evaporation beneath the canopy, among others (Drexler et al., 2004; Yan et al., 2012).

Nevertheless, Priestley Taylor (PT) model has achieved sound results in flooded ecosystems (Drexler et al., 2004; Sun & Song, 2008), and may obtain adequate λE estimates even in areas lacking specific meteorological inputs, in combination with remote sensing data (García et al., 2013). Additionally, the Priestley Taylor- Jet Propulsion model (PT-JPL) (Fisher et al., 2008), later modified by García et al., 2013, allows for a more extensive use of this model, as no field calibration or water vapor deficit estimates are needed. However, some modifications may be required in this model to account for variations in soil moisture and evaporation beneath the canopy, which have an important effect in global evaporation rates (Yan et al., 2012). There are not many works to estimate ET in rice fields based on a combination of RS data and λE models (Chemin and Honda, 2006; Narongrit & Chankao, 2009; Lal et al., 2012) and none of them has explored the potential of two source models in rice ecosystems. Thus, PT-JPL model provides a promising approach to estimate spatial variations of ET in rice ecosystems while maintaining simplicity and low necessity of external parameters. The use of this model combined with MODIS time series data would also allow the study of temporal patterns and periodicity, revealing meaningful information of rice ecosystem dynamics.

1.7 Time series analysis of remote sensing data in rice fields

Time-series analysis of remote sensing data provides important information to assess ecosystem dynamics (Zhang et al., 2003). It has been widely used to study seasonal behaviour and dynamics in natural variables (Huesca, 2012), and particularly in the study of long-term variations of ET (Moyano et al., 2015). The use of spectral indices time series is also a solid approach to identify intra-annual and interannual dynamics, and has been applied in the fields of land-use identification, phenology detection and natural phenomena monitoring, among others (Gumma et al., 2014; Shihua et al., 2014; Simonneaux et al., 2008). Statistical time series analysis of remote sensing images has also a relevant application in environmental monitoring (García et al., 2010; Huesca, 2012). Particularly, the Autocorrelation Function (ACF) (Box et al., 1994) may provide meaningful results assessing the stability of temporal patterns in terms of seasonality and periodicity (Dornelas et al., 2013) and in identifying vegetation patterns (Setiawan et al., 2014). Thus, the application of ACF to study spectral indices time series in rice fields may provide relevant information in relation with vegetation and water dynamics.

In the present dissertation, a methodology is proposed to monitor water and vegetation dynamics in rice ecosystems based on spectral indices time series, and the use of remote sensing time series in combination with ET models. The options explored are intended to be applied with low field-data requirements and inputs, aimed to be feasible in regions lacking general agricultural information, and especially in developing countries.

1.8 Objectives and Structure

1.8.1 Objectives

The aim of this thesis is the development of methodologies to use remote sensing time series and spectral indices to monitoring vegetation and water management dynamics in rice ecosystems, minimizing the needs of field data. We used MODIS time series to achieve results with enough time frequency and adequate spectral bands to detect both water and vegetation phenomena.

The specific objectives are the following:

- To explore the potentiality of Spectral Indices annual time series to map rice ecosystems based on the identification of rice patterns and distinguish them from other land uses with similar characteristics,
- To assess the potential of different spectral indices for monitoring rice phenology and flooding dynamics by combining phenometric and statistical time series approaches.
- To evaluate the PT-JPL daily model performance in obtaining λE estimates in rice ecosystems and introduce an adaptation for the variable soil conditions present in flooded ecosystems.

1.8.2 Structure of the thesis

Chapter 1 introduces the general importance of adequate water management monitoring in rice ecosystems and the role of remote sensing time series and spectral indices to address this challenge. The key features of rice plant phenology, distribution and water management practices are described to understand the application of remote sensing techniques. The three study zones are presented and their similarities and differences in terms of agricultural and water management practices are explained.

Chapter 2 assesses a methodology to identify and map rice areas with low field data requirements, based on the use of MODIS spectral indices time series and spectral matching techniques.

Chapter 3 analyse the performance of four spectral indices in detecting key phenological and flooding events in rice ecosystems under different water management practices, and a specific combination of indices for detecting rice flooding events and phenological stages is proposed.

Chapter 4 explores the adaptation of the PT-JPL-daily model to rice ecosystems in two coastal locations of the Mediterranean Region in order to obtain estimates of ET dynamics with low requirements of in situ data, to allow the potential use of this model in locations with a limited disposition of field data.

Chapter 5 summarizes the general conclusions of this dissertation and the proposed methodology to identify rice areas and flooding periods as a basis to be used in order to estimate water needs and dynamics in rice ecosystems.

1.9 Study areas: the Ebro Delta, the Albufera Natural Park and Orellana.

Three rice zones in the Mediterranean Region have been included in this work. Two of them, the Ebro Delta and the Albufera Natural Park, are coastal rice areas with similar flooding regime: agricultural flooding during the rice cycle and an additional winter flooding after the harvest. The third one, Orellana, is an inland rice area with a single flooding period, followed by bare-soil conditions during the winter. These variations have been used to assess differences in the performance of the methodologies proposed depending on the particularities of water management options in rice paddies.

More detailed descriptions of the study zones are included in each chapter.

CHAPTER 2

Evaluation of spectral indices time series for mapping rice ecosystems in the Mediterranean Region.

Chapter 2. Evaluation of spectral indices time series for mapping rice ecosystems in the Mediterranean Region.

2.1. Introduction

On the light of recent international developments, such as the Sustainable Development Goals (SDGs) of the 2030 Agenda and the Paris Agreement, there is a need to monitor and report accurately any spatial variable with strong implications in food security, water usage and climate change. Rice fields are key for food security, providing staple food for almost half of the world's population (Kuenzer and Knauer, 2013). They also have strong implications for natural resource management due to the large quantities of water needed in rice cultivation, having important effects in water demand and quality (Xiao et al., 2006). In addition, the maintenance of flooded soils constitutes an important source of methane emissions (Gon et al., 2000). Thus, counting on reliable information on rice field distribution is crucial to assess the status of food security and environmental sustainability (Boschetti et al., 2014) at regional and global scale.

Recently, there have been dramatic changes in rice field distribution as a consequence of agricultural expansion (Zhang et al., 2015; Maila, 2016; Zhang et al., 2017), urban development and shortage of resources due to climate change (Dong et al., 2009; Wang et al., 2015; Torbick et al., 2017). In this sense there is an urgent need to mapping rice fields, and to developing methods for monitoring and updating rice field maps in order to account for rapid changes on rice fields distribution worldwide (Dong et al., 2015; Wang et al., 2015).

Traditionally, statistical crop data has been the most extended approach to monitoring rice fields distribution in many regions and at global scale (Frolking et al., 2002; Monfreda et al., 2008), although they are insufficient in spatial and temporal detail (Gumma et al., 2014) and the data are rarely available in a timely manner (Gumma et al., 2011). In response to this challenge, remote sensing techniques can rapidly provide up-to-date maps of rice areas at large scale (Gumma et al., 2011; Qin et al., 2015; Zhang et al., 2017). Remote sensing have been widely used to map rice fields in the last decades. In regions dominated by cloudy skies, microwave capacity to penetrate through clouds has been crucial to produce good-quality rice maps (Bouvet et al., 2009). However, their limited availability (Zhang et al., 2009) and costs (Li et al., 2012) have restricted their large scale usage. Optical remote sensing has been widely applied in numerous studies. The different methodologies developed in the last decades have included the use of several radiometric, spatial and temporal resolutions, combined with different classification schemes, research aims and validation intensities (Turner & Congalton, 1998; Xiao et al., 2005; Sun et al., 2009; Nuarsa et al., 2012; Gumma et al., 2014). Optical remote sensing imagery was firstly applied in rice mapping in the 1980s, with approaches based on the band reflectance of single or multiple Landsat images, using supervised or unsupervised classifiers (McCloy et al., 1987; Fang, 1998). However, the Landsat long revisiting cycle, and consequently the lack of data availability in relation with cloud-induced noises, has limited its use (Dong & Xiao, 2016). In the 2000s, the launching of the MODerate Resolution Imaging Spectroradiometer (MODIS) sensor, with daily revisit frequency and specific bands to detect water and vegetation, led to the development of improved methodologies for rice mapping. Those features were used to develop approaches based on time series and the phenological characteristics of rice (Sakamoto et al., 2005; Xiao et al., 2005). Among them, threshold-based methodologies, relying on the relations among vegetation indices

(VIs) in rice has been applied in multiples studies (Xiao et al., 2006; Shi et al., 2013; Qin et al., 2015). In particular, the subtraction-based algorithm (SBA), based on the difference between Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) and the Land Water Algorithm (LSWI) has been applied for mapping rice fields in Asia (Xiao et al., 2005; 2006; Zhang et al., 2017). The best results were achieved in southern regions, with no snow cover that may complicate the classification process (Zhang et al., 2015). Although this methodology has proved to be suitable in several regions, there are some limitations in its use, mainly in relation with cloud contamination and extreme rainfall events during planting dates, rice field size and wetland misclassification (Sun et al., 2009; Dong & Xiao., 2016)). Additionally, its application in the Mediterranean Region showed high commission errors (Manfron et al., 2012.)

Other approaches are based on the assessment of annual profiles of rice VIs with spectral-matching techniques (SMTs) (Thenkabail et al., 2007; Gumma et al., 2011, 2014). In many studies, this type of methodologies has been directly applied through the annual NDVI or EVI time series with meaningful results in South Asia (Sakamoto et al., 2005) and Bangladesh (Gumma et al., 2015). However, these techniques based on NDVI or EVI annual profile could be potentially difficult to apply extensively due to the diversity in rice cropping systems (Dong & Xiao, 2016), and intra-class variability of temporal profiles could induce misclassification (Lunetta et al., 2010). In this regard, the use of other spectral indices, with potential to discriminate accurately rice phenological patterns from other land use patterns will be extremely advantageous.

Since intermittent flooding, vegetation periods and dry bare soil constitute distinctive phases in rice phenology, spectral indices sensitive to both vegetation and water are crucial for reproducing clearly rice phenological profiles (Sari et al., 2010). Although NDVI has shown sensitivity to soil wetness (Motohka et al., 2009), there are other indices combining Shortwave Infrared (SWIR) bands that have demonstrated their outstanding capacity to detect rice phenological events and hydroperiod (Boschetti et al., 2014). Spectral Shape Indices (SSI) combine the angles formed by consecutive bands to reproduce coarsely the behaviour of a specific region of the spectrum (Palacios-Orueta et al., 2006). In particular, recent studies have successfully applied SSI combining the angles formed by Near Infrared (NIR) and SWIR bands to reproduce crop phenology and soil water content patterns (Das et al., 2013; Tornos et al., 2015). The Shortwave Angle Slope Index (SASI) (Khanna et al., 2007), based on the angle and slope between NIR, SWIR1 and SWIR2, has showed strong potential to discriminate land cover types as well as soil and vegetation moisture content in laboratory. Murthy et al., (2012), assessed SASI potential to track surface wetness and rice transplantation pattern in irrigated areas and detected that SASI enables higher discrimination of rice classes compared to NDVI and NDWI. Das et al (2013) studied the potential of SASI to determine soil dryness and wetness in crops through threshold values, and Tornos et al. (2015) demonstrated the utility of this index in determining specific phenological phases in rice, such as flooding and harvesting. Thus, SASI index could potentially show a distinct annual pattern for rice stages, including bare soil and flooded soil phases, which may be used to discriminate rice areas in a categorical manner.

Although many efforts have been made to map rice areas by using different algorithms and data sources, there is no availability of global or regional paddy rice maps produced with enough frequency (Dong & Xiao., 2016) to fulfil the monitoring needs at global level. The analysis of new spectral indices more appropriate for rice identification and their application in simple

methodologies, with low requirements of field data, may contribute to provide accurate and updated data on rice field distribution and changes.

In this study, we have explored the potential of SASI annual time series to identify rice patterns and distinguish them from other land uses with similar characteristics, such as wetlands. We have studied the use of SASI and compared its performance with NDVI, a well-known index usually applied in rice mapping approaches, in two coastal locations and an inland location in the Mediterranean Region. The main objective was to evaluate a quick, accurate and simple methodology, based on VIs time series, to identify rice fields and develop rice maps that can be timely updated in the long term for land use monitoring purposes.

The specific objectives of this study were:

- Assess the potential of SASI time series to identify rice fields from other land uses in coastal and inland areas with different flooding dynamics in the temperate region.
- Evaluate the performance of SASI and NDVI in those locations.
- Analyse the accuracy of a quick-mapping method based on spectral indices annual profiles.

2.2. Study sites and data

2.2.1 Study sites

The Ebro Delta and The Albufera Natural Park rice areas are ecosystem with similar natural conditions. They are coastal rice paddies close to lagoons and natural wetlands in the Mediterranean Region. In both areas the rice fields are kept flooded the main part of the year, firstly during the rice growing period and secondly during the winter environmental flooding. The third study area, Orellana, is an inland irrigation district surrounded by other agricultural areas growing different crops, including rice.

The Ebro Delta

The Ebro Delta, located in the North-East of Spain (Fig. 2.1), is a coastal region devoted to rice production and wetland protection. The climate is Mediterranean, with annual mean rainfall of 556 mm, an annual mean temperature of 18° and a dry summer. The total extension of the Delta is 32000 ha, being 21500 ha of them rice fields. Natural wetlands and lagoons cover a considerable area of the Delta, nearly 7700 ha. Two of the main lagoons are placed in the southern part of the Delta, while the other is in the north-western part. Additionally, some urban areas are located in the Delta, being Deltebre, in the middle of the Delta, the most relevant. The Delta is surrounded by the Mediterranean Sea except for its western border. Land uses in this zone are mainly agricultural land (other crops) and natural areas.

Fig. 2.1. Study area: The Ebro delta, Catalonia (Spain).

Rice fields are kept flooded for most of the year to avoid salinization from a saline aquifer and also to provide an adequate habitat for the protected fauna. The flooding of the fields begins the third week of April, following a strict schedule. The rice is usually sown during the two first weeks of May, with plant emergence starting at the end of the month and reaching the heading date stage by late July. After this moment, the rice develops panicles while the vegetative growth ceases completely. The harvest takes place the first half of September, and is followed by a new flooding period with environmental purposes, starting the first week of October. The environmental winter flooding period takes place until the end of January and nearly one month is needed to completely dry the paddy fields. After that, the fields remain bare and dry until the beginning of the rice cycle in late April, except for some spring rainfall events.

The Albufera Natural Park

The Albufera Natural Park is located in the eastern coast of Spain (Fig. 2.2). It is a 21000 ha wetland ecosystem, including a mixture of approximately 14500 ha of rice fields, a 2800 ha lagoon in the northern part and natural areas close to the coastline (Generalitat Valenciana, 2002). The whole area is surrounded by urban areas and other crops. The climate is Mediterranean, with similar features than those in the Ebro Delta. The precipitation is normally between 400-500mm, and it is mostly concentrated in autumn and spring. The rice phenological cycle begins with the flooding of the fields the first week of May. Rice is usually sown the 10th-15th of May and plant emergence begins at the end of the month. The fields are completely covered by a rice canopy between June and July and the harvesting takes place at some point in September, after draining the fields. In October the rice fields are flooded again, keeping an open water table until February. After that moment, the fields are drained and the soil is completely dry at the end of March.

Fig. 2.2. Study area: The Albufera, Valencia (Spain).

Orellana

The Orellana irrigated area is an inland agricultural zone close to Guadiana River, in the South-West of the Iberian Peninsula (Fig. 2.3). Although several crops are grown, some districts are mainly covered by rice fields with only occasional zones covered by other irrigated crops. The climate is Mediterranean with continental influences, lacking the effect of the coastal influences present in the Ebro Delta and the Albufera Natural Park. The study site is an 8500 ha district mainly covered by rice fields and surrounded by other districts with a variety of crops, including rice. The northern part is close to forests and shrublands. The flooding of the fields takes place between the last week of April and the second week of May, depending on weather conditions. The rice fields are kept flooded with a 5 cm water table for all the rice cycle, until the end of September. The phenological stages and dates are similar to those in the Albufera and the Ebro Delta, with some variations due to climatic differences. In this zone, however, the fields are drained after harvest and the soil is kept bare and dry until the next year.

Fig. 2.3. Study area: Orellana, Extremadura (Spain).

2.2.2 Data sources

This study was based on the MOD09A1 dataset for the year 2012. This product consist of an 8-day MODIS composite at 500-meter spatial resolution. The dataset of 552 images includes reflectance values for Bands 1-7: Blue (450 nm), Green (555 nm), Red (645 nm), NIR (860 nm), SWIR1 (1240 nm), SWIR2 (1640 nm) and SWIR3 (2130 nm). It also contains quality control flags, sensor zenith angles and observation dates per pixel. The dataset was downloaded from the MODIS website (<http://redhook.gsfc.nasa.gov/>) and re-projected using the MODIS re-projection tool (<http://edc.usgs.gov/programs/sddm/modisdist/>) to UTM zone 30. Quality flags were decoded using LDOPE software. Abnormal values from low-quality pixel values were eliminated using MODIS quality data bands. Cloud-contaminated pixels were also removed based on the internal cloud algorithm flag of MOD09A1.005 500-meter Surface Reflectance Data State QA. An outlier filter was also used to identify and remove values outside the range of the mean plus/minus twice the standard deviation within a five-date period window. Missing data were filled with the average of the previous and subsequent date values in the time series.

Rice masks, crops calendars, as well as descriptions of agricultural and water management practices in the three study areas were provided by water user associations, CEDEX (Ministry of Public Works), “Confederación Hidrografica del Guadiana” (Ministry of Agriculture) and CEAM (Mediterranean Center for Environmental Studies).

2.3. Methodology

2.3.1 Computation of spectral indices

The, NDVI (equation 2.1), is a well-known vegetation index, based on the normalized difference between NIR and Red bands. It has been used to detect the heading date in rice (Wang et al., 2012) and for monitoring rice phenology.

$$NDVI = (\rho_{NIR} - \rho_{RED}) / (\rho_{NIR} + \rho_{RED}) \quad (2.1)$$

The second index, SASI, is a spectral shape index (SSI) originally developed to discriminate among dry soil, wet soil, dry and green vegetation (Khanna et al. (2007)). It combines information from NIR, SWIR1 and SWIR2 MODIS bands and relies on the variations of the angle formed by SWIR 1 vertex with NIR and SWIR2 in the spectrum, emulating the shape of this region of the spectrum (Fig.2.4). It is defined as the product of the SWIR1 angle (β_{SWIR1}) and the slope of the line “c” that links reflectance (R) at NIR and SWIR2 vertices. The equations for calculating SASI are described in equation 2.2, 2.3 and 2.4. A more detailed explanation of them, as well as the complete description of this index can be found in Khanna et al. (2007).

$$\beta_{SWIR1} = \cos^{-1}[(a^2 + b^2 - c^2) / (2 * a * b)] \quad (2.2)$$

$$Slope = (R_{SWIR2} - R_{NIR}) / d \quad (2.3)$$

$$SASI = \beta_{SWIR1} * Slope \quad (2.4)$$

Fig. 2.4. Relationship between angle β_{SWIR1} formed at SWIR1 and the slope of line c. Spectral values have been forced to coincide at SWIR1 to illustrate the relationship between angle and slope in SASI (adapted from Palacios-Orueta et al., 2006). a, b, c and d are referred to the Euclidean distances between the wavelength and reflectance at NIR (RNIR) and SWIR2 (RSWIR2).

Slope c takes positive values for dry soils and decreases for wet soils. Vegetation residues and dry vegetation hold a slope close to zero, and takes negative values for green vegetation. The value of angle β_{SWIR1} , also named AS1 in other works (Palacios-Orueta et al., 2012), is typically large for green vegetation and dry soils, and smaller for wet soils and dry vegetation. In line with this, the product of the angle and slope is positive and large in value for dry soils, and negative and large in absolute value for green vegetation. For dry matter, SASI takes values close to zero, as both the angle and the slope are small. In wet soils, the index is positive but small due to a decrease in the value of β_{SWIR1} .

The time series for each reflectance band were compiled, and the indices were calculated for the whole study period using ENVI4.5.

2.3.2 Data analysis

The methodology used in this work is based on the specific rice annual dynamics showed in spectral indices time series, with distinct annual patterns in rice areas strongly different from those of any other land use.

A time series from a single rice pixel was selected as a reference profile to identify the standard NDVI and SASI intra-annual dynamics. To map rice fields, a profile similarity comparison method, the Spectral Angle Mapper (SAM) (Kruse et al., 1993), was accomplished between the reference profile and every time series in the study area. In this method the NDVI and SASI time

series are considered as vectors with a dimensionality equal to the number of observations, thus the difference in shape between two annual profiles is calculated as the angle between two vectors, i.e. the angular distance. The SAM analysis was performed for the 2012 annual time series. This approach would potentially determine rice areas in a particular year. The angular distances values on a pixel basis were classified in four categories. Small angular distances indicated a high similarity with the reference profile and thus those pixels were identified as rice-fields.

Validation in the Ebro Delta

The identification of rice field pixels for the year 2012 was validated using the rice mask provided by the Ebro Delta Water Users Association. A confusion matrix was accomplished within an area of 1886 pixels (47150 ha) in which 47.4% was occupied by rice fields. Other land uses in the area were natural wetlands, lagoons, other agricultural land, forest, urban areas and the sea.

Validation in the Albufera Natural Park

In order to assess the effectiveness of this methodology in other rice areas with similar ecological conditions, the same reference indices profiles and angular distances classification categories from the Ebro Delta were applied to the Albufera Natural Park. The results of the mapping process were compared with an orthophoto of the Albufera rice paddy area and with crop surface statistics from this zone (Generalitat Valenciana, 2002).

Validation in Orellana

Due to the distinct rice annual dynamics in Orellana (lacking the winter flooding period) site-specific reference profiles were selected. This irrigation district shows higher spatial variability, with rice fields intermingled with other irrigated crops. A rice mask for this district, provided by the Confederación Hidrográfica del Guadiana, was used for validation. Other rice fields belonging to different irrigation districts have not been included in the validation process.

2.4. Results

2.4.1 Rice mapping in the Ebro Delta for 2012

The rice mask was used to select the reference pixel and to establish the range of angular distances associated to rice pixels. Fig 2.5.a and 2.5.b showed the histograms of angular distances between the reference rice profile and each one of the pixel profiles in the study area. The lower angular distances were classified into three equal categories while large angular values were classified in a wider class.

Fig 2.5. Histograms of angular distances in radians in the Ebro Delta for NDVI (a) and SASI (b) in 2012

The pixels located into the first class, ranging from 0 to 0.35 in NDVI and to 0.45 in SASI, were identified as rice while the rest of the pixels in other categories corresponded to other land uses. The dynamic range of values in SASI was larger than in NDVI, with most of the non-rice pixels taking values between 1.4 and 2.5.

Figures 2.6.a and 2.6.b show a map based on NDVI and SASI angular distances with rice in green (i.e. lower angular distances), and the other three classes in yellow orange and red respectively.

Fig. 2.6. Rice field maps based on NDVI (a) and SASI (b) annual patterns in the Ebro Delta (2012). The rice mask is represented by the black polygons.

NDVI angular distances for rice fields (in green) were consistently lower than those for other land uses (in yellow, orange and red). In the map, land uses such as lagoons, urban areas, other agricultural lands and natural areas showed intermediate values being assigned to the yellow category (Fig 2.6.a). Sea pixels showed the highest angular values being labelled in red. The SASI index discriminated more clearly rice pixels from the rest of land uses than NDVI (Fig. 2.6.b). A large part of the study area, covered by different land uses, showed large angular distances being assigned to the red class. Lagoons were the land use closer to rice fields with values classified in the yellow and orange categories (Fig 2.6.b).

Figures 2.7.a and 2.7.b show an example of the NDVI and SASI annual profiles for each category, with green colour associated to the pixels with lower angular distances. SASI annual dynamics in rice (Fig. 2.7.b) showed a period of distinct high values between February and April, when the soil is dry, clearly different from all the other land uses.

Fig. 2.7. Examples of NDVI (a) and SASI (b) annual patterns for each category in the Ebro Delta. Green colours indicate annual profiles similar to the reference rice profile.

To assess the results, a confusion matrix (Table 2.1) was constructed for a zone with the same area occupied by rice fields and by other land uses. SASI showed an overall accuracy slightly higher than NDVI, with better identification of the rice fields; on the other hand both indices showed a similar performance identifying non-rice pixels.

SAM classification	Groundtruth data		
	Rice	Non-Rice	Producer accuracy (%)
NDVI			
Rice	840	105	88.89
Non-rice	40	898	95.73
User accuracy NDVI (%)	95.46	89.53	
Overall accuracy: 92.40			
SASI			
Rice	851	94	90.05
Non-rice	43	898	95.43
User accuracy SASI (%)	95.19	90.52	
Overall accuracy: 92.80			
Notes: counted in number of pixels			

Table 2.1. Accuracy assessment of the SAM classification for NDVI and SASI in the Ebro Delta (2012).

2.4.2 Rice mapping in the Albufera Natural Park for 2012

The classification methodology developed for the Ebro Delta was applied in the Albufera Natural Park to test the potential of this procedure in other rice areas with similar ecological conditions.

(a)

Fig 2.8. Histograms of angular distances in radians in the Albufera Natural Park for NDVI (a) and SASI (b) in 2012.

The annual time series of NDVI and SASI for 2012 were compared with the annual pattern obtained in a ground truth rice pixel in the Ebro Delta, and classified in the same manner (Fig. 2.8). In this case, the dynamic range of values in SASI was also wider in SASI than in NDVI. The pixels classified in the first category (rice pixels) showed higher angular distance values in comparison with the values obtained in the Delta in both histograms (Fig. 2.8a and 2.8b).

Fig. 2.9. Rice field map based on NDVI spatial variations in the Albufera Natural Park (2012) (a) and orthophoto with the delimitation of the Albufera rice field area (b).

The results obtained were compared with an ortophoto of the zone where rice fields have been identified by photointerpretation, and also compared with rice field area statistical data.

The pixel classification based on NDVI for 2012 (Fig. 2.9a) identified correctly the rice pixels (in green) from the surrounding areas. The area occupied by the Albufera Natural Park is clearly identified in the classification process. Additionally the lagoon, placed in the upper part of the zone, was correctly differentiated from rice fields and was classified into other categories (in orange and red). In line with the results obtained for the Ebro Delta, non-rice pixels were mostly classified in the yellow category, except for the sea pixels, included in the red category.

Fig. 2.10. Rice field map based on SASI spatial variations for the Albufera Natural Park (2012) (a) and orthophoto with the delimitation of rice field area (b).

When using SASI, the limits of the rice area of the Albufera Natural Park were also correctly identified (Fig. 2.10.a and 2.10.b). Only a few pixels, in the limits of the rice area and in the lagoon were classified in the yellow class; it is likely that these areas correspond to mixed pixels. The surrounding areas with distinctively higher SAM values were more clearly discriminated from rice field pixels, being classified into the red and orange categories.

Fig. 2.11. Examples of NDVI (a) and SASI (b) annual patterns for each category in the Albufera. Green colours indicate annual profiles similar to the reference rice profile.

Figures 2.11.a and 2.11.b show examples of pixels annual patterns in each category. The annual pattern of pixels identified as rice, in green, are similar to those in the Ebro Delta.

Accuracies of 98.1% and 77.24% for SASI and NDVI respectively were shown when comparing total areas covered by rice with statistical data in the study area.

2.4.3 Rice mapping in Orellana for 2012

In Orellana, the annual profiles of NDVI and SASI were compared with a reference rice profile from the same area. The pixels were also classified in four categories, based on the results within the Orellana validation mask (Fig. 2.12).

Fig 2.12. Histograms of angular distances in radians in Orellana for NDVI (a) and SASI (b) in 2012.

Angular distances dynamic range was higher in SASI than in NDVI (Fig. 2.12), even in land uses with patterns similar to those of rice fields, such as irrigated crops. The level of identification of rice fields within the validation area was 82.77% and 90.08% for NDVI and SASI respectively (Fig. 2.13.a and 2.13.b). This indicates a higher discrimination potential in SASI.

Fig. 2.13. Rice field maps based on NDVI (a) and SASI (b) annual patterns for the Orellana (2012). The rice mask is represented by the black polygons.

Outside the validation mask, rice pixels were classified in the first category (green), with both indices while pixels corresponding to other crops and natural areas were classified in the second and third categories (yellow and orange).

Fig. 2.14. Examples of NDVI (a) and SASI (b) annual patterns for each category in Orellana. Green colours indicate annual profiles similar to the reference rice profile.

In this zone flooding dynamics are notably different to those in the Ebro Delta and the Albufera, as rice fields are not flooded during winter. Thus, NDVI and SASI annual values presented a different pattern from those of the other two zones (Fig. 2.14).

2.5. Discussion

In this study, the potential of two vegetation indices to identify rice field areas based on their distinctive annual pattern has been assessed. The procedure was validated in a rice coastal area, and applied in other rice area with similar ecological conditions. Vegetation and flooding dynamics in these areas are similar, although some differences in phenological dates and in the flooding

regime, including water levels in the fields, were expected. Additionally, this method was also evaluated in an inland rice area with different flooding dynamics.

The NDVI annual profile in rice fields during the growing season showed a similar pattern in the Ebro Delta (2.7.a) and the Albufera (2.11.a) due to the similarity in the vegetation and water dynamics between the two zones. The NDVI increased quickly since flooding (May) until the heading date (end of July), and then decreased until the harvest (middle September). It did not show a distinct trend during the non-growing season, when the soil is flooded first (October) and is drained afterwards (February). On the other hand SASI (2.7.b and 2.11.b), showed an abrupt increase in coincidence with the draining of the fields (at the end of January) after the winter flooding, in both study areas. This indicates a higher sensitivity of SASI to soil moisture content than NDVI, being able to discriminate bare soil from flooded soil. Other studies have showed similar results in rice fields (Tornos et al., 2015) as well as in other situations (Khanna et al., 2007; Das et al., 2013).

The histograms of NDVI (2.5.a, 2.8.a) and SASI (2.5.b, 2.8.b) angular distances in the Ebro Delta and the Albufera presented a similar distribution of values. In both cases SASI angular distances for all land uses were distributed in a larger range than NDVI angular distances, indicating a higher variability of SASI annual patterns among different land uses. Moreover, while in NDVI angular values for most of non-rice pixels were close to those from rice pixels (Fig 2.5.a and 2.8.a), in SASI most non-rice pixels were located in the fourth class (Fig 2.5.b and 2.8.b). This allows for a more clear segmentation between rice pixels and non-rice pixels and indicates a better discrimination potential.

The classification scheme was assessed inside and outside the validation area in the Ebro Delta, and was applied directly in the Albufera Natural Park, where wetlands and a lagoon occupy a significant proportion of the area close to rice fields. The confusion matrix in the Delta showed that SASI achieved slightly better results (Table 2.1) than NDVI. The accuracy of the results was better or similar to those found in other works (Gumma et al., 2011; Asilo et al., 2014), even in those with higher spatial resolution (Dong et al., 2015; Torbick et al., 2017). In the Albufera, the comparison between the estimates of rice area and crop statistical data showed that the performance of SASI (98% of accuracy) was clearly better than NDVI. Additionally, SASI maps (2.6.b and 2.10.a) showed a large area occupied by the red class corresponding to non-rice land uses. This feature would be highly useful when applying the methodology in other regions with different land uses.

SASI number of errors was lower than NDVI, surely due to its capacity to discriminate more clearly soil and vegetation dynamics, and specially flooded soils (Tornos et al., 2015). The errors of misclassification were mainly due to mixed pixels near the lagoons or close to other crops, both

in inner zones and in frontier pixels. Consequently, increasing the spatial resolution of the images could decrease the number of errors.

The three main lagoons and wetlands in the Ebro Delta were classified as non-rice pixels by both indices (Fig. 2.6.a and 2.6.b), being more clearly discriminated by SASI. Thus, this index distinguished appropriately rice pixels from wetland pixels, which presents a temporal profile that can be easily confused with rice profiles in rice mapping procedures (Dong & Xiao, 2016). NDVI (Fig. 2.6.a) failed to detect rice fields in mixed pixels outside the Ebro Delta, while SASI (Fig. 2.6.b) detected clearly some existing rice fields in the bank of the river.

In the Albufera, NDVI failed to identify some paddies within the rice area (Fig. 2.9.a). In this zone is a common practice increasing the water level in some fields for recreational activities, which can result in abnormally lower values of NDVI in coincidence with the winter flooding. On the other hand, SASI was not as affected by changes in water level or phenological date shifts between rice fields resulting in a more accurate identification of rice fields. Accordingly, it can discriminate more clearly rice pixels from other land uses even when some phenological and flooding changes take place. This feature may be useful to identify rice areas with flooding periods out of the growing cycle and different water levels in the rice fields, common in other regions (Berg et al., 2002; Lu & Li, 2006).

In Orellana results were slightly poorer than in the Ebro Delta and the Albufera, presenting more misclassification errors in rice identification mainly in frontier pixels (Fig. 13.a and 13.b). The accuracy within the validation zone achieved with SASI (90.08%) was better than the accuracy level obtained with NDVI (82.77%). Still both results could be considered satisfactory taking into account the high frequency of coexistence of more than one crop within MODIS pixels, both in frontier pixels and inside the irrigation district.

In this area NDVI (Fig. 2.14.a) and SASI (Fig. 2.14.b) presented similar dynamics than in the other two sites during the rice growing period (from May to middle September). On the other hand, in winter (October to April) indexes showed a different behaviour, as no winter flooding takes place. The lack of winter flooding could increase the difficulty to distinguish rice from other crops located in irrigation districts surrounding the study area.

Still, SASI showed better results than NDVI in this zone. The NDVI angular distances (Fig. 2.12.a) were distributed in a narrower range than in the Ebro Delta and the Albufera (Fig. 2.5.a and Fig. 2.8.a), while SASI (Fig. 2.12.b) presented a similar distribution in the three areas (Fig. 2.5.b and 2.8.b), indicating higher variability and better discrimination potential. NDVI had more difficulties in discriminating rice patterns from other land use patterns, and thus more misclassification errors occurred. SASI performed better in discriminating rice fields from other irrigated crops (some of them with single-cycle and similar seasonality). This proves that SASI rice annual patterns are

highly distinct from those in other land uses, even without winter flooding dynamics. This capability relies on SASI different values in bare soil and wet soil (Khanna et al, 2007).

In general terms, this approach may produce adequate estimates of rice field area if used at appropriate scale, providing a basis for other rice studies such as flooding monitoring and water use monitoring and planning.

The similarity of NDVI and SASI patterns between the Ebro Delta and the Albufera made possible to use the same classification scheme and even the same reference profiles. This indicates that this scheme could be applied to other areas with similar annual dynamics, very common in many Asian countries (Kurechi, 2007; Wood et al., 2011). The results in Orellana indicate also a better potential of SASI in areas without winter flooding. SASI showed a better capacity to differentiate soil and water dynamics, which is crucial to capture rice field changes through the year.

The proposed approach constitutes a simple procedure to map rice areas in different environments and it holds potential to be extended to other regions. The extension of these results to other regions is possible for zones with similar flooding and vegetation dynamics. However, a methodology to systematically classify SAM values in different categories should be explored in order to simplify the proposed procedure. In other regions with different vegetation and flooding dynamics it is essential to count on a reference rice annual profile within the study area, or from other area with similar annual dynamics.

Although this method based on MODIS images is specially indicated for rice mapping in medium-size rice areas or regional studies, the use of higher spatial resolution sensors should be explored for studies in small-size rice areas. In this regard, the increasing availability of data and resolutions from new sensors, such as the new ESA Sentinel-2 sensors (Druch et al., 2012) may provide the opportunity to improve the results obtained.

2.6. Conclusions

This study explored the potential of two spectral indices, NDVI and SASI, to identify rice areas with a procedure based on the detection of similar annual time series profiles with spectral matching techniques. The procedure was tested in two coastal rice areas close to wetlands and in an irrigation district surrounded by other irrigated crops. Both indices clearly demonstrated their potential to provide accurate rice maps in rice areas with different phenological and flooding dynamics, obtaining higher levels of accuracy with SASI in both cases. The overall accuracy was 92.8%, 98.1% and 90.1% for SASI and 92.4%, 77.24% and 82.8% for NDVI in the Delta, Albufera and Orellana respectively. These results confirm the potential of vegetation indices to provide reliable rice maps and highlight the importance of exploring angular indices to improve the identification of land cover dynamics. In particular, the use of SASI has demonstrated its potential

to provide remarkable results in discriminating rice from other crops or land uses, in combination with spectral matching techniques.

The main findings of this work were:

- The combined use of annual NDVI and SASI time series with SAM constitute a rapid, transparent and accurate procedure to identify rice areas with similar vegetation and flooding dynamics.
- SASI provides better information on transitions in soil and vegetation moisture which is an asset in rice fields as they are a dynamic system of soil, free water and green vegetation.
- SASI annual profiles capture more accurately rice dynamics than NDVI in the study zones, outperforming in discriminating between rice fields and land uses with similar dynamics, such as wetlands and irrigated annual crops.
- This procedure can be directly applied with adequate levels of accuracy after validation in other zones with similar flooding and vegetation dynamics, although some kind of validation procedure within the study site is recommended.

Accurate and simple rice mapping techniques are needed to provide adequate estimates of rice field area, due to the importance of rice in food security and for its environmental significance. The application of this approach based on MODIS time series may provide the opportunity to count on annual rice maps at global level from 2000 to the year in course. The results obtained in this work may be used as the basis for other rice studies, such as flooding, phenology or evapotranspiration monitoring in rice fields. In a global context of water scarcity, climate change and land use change, this approach may provide a potent tool for natural resource management, monitoring and planning, especially in countries lacking reliable field or statistical data.

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CHAPTER 3

Assessment of MODIS spectral indices for determining rice paddy agricultural practices and hydroperiod.

Chapter 3. Assessment of MODIS spectral indices for determining rice paddy agricultural practices and hydroperiod.

3.1. Introduction

Approximately 180 million ha are under rice cultivation worldwide, and 442,000 ha are located in the European Union (MAPAMA, 2017). Sustainable rice farming plays a key role in food security; according to the United Nations, more than 50 percent of the global population depends on rice for approximately 80 percent of its food requirements (FAO, 2002.b). Moreover, rice fields represent an important aquatic ecosystem, hosting a large variety of terrestrial and aquatic species (FAO 2013) that typically remain flooded during the growing season. Despite the positive functions of rice systems, such systems also cause environmental degradation (Van Niel and McVicar, 2004). Rice water consumption and greenhouse gas emissions from paddy fields are especially critical issues (FAO, 2013). In upcoming years, the world will face the challenge of meeting global demands for rice while preserving land and water resources. Thus, monitoring these systems will become essential at both the local and global scale (Kerr et al., 2003).

Phenological data are used to estimate net primary production (Kimball et al., 2004), crop growth and yield (Bauman et al. 2001). These data may also be used to determine time boundary conditions in crop yield models (Bauman et al., 2001), to examine animal dynamics in crop-associated fauna (Pettorelli et al., 2005) and to support water management decisions (Dingkuhn and Gal, 1996). Moreover, rice hydroperiod determination as part of the rice growing cycle is vital to rice monitoring and impact management and is expected to become more relevant in the near future (Torbick et al., 2011; Boschetti et al., 2014). This is particularly true in studies that examine rice paddy methane emissions (Xiao et al. 2005). The importance of rice water table depth and phenological fluctuations in methane (Meijide et al., 2011) illustrates the necessity to develop accurate rice agricultural and hydroperiod monitoring techniques.

Traditional studies focusing on phenology involve conducting on-site ground observations (Tang et al., 2009, Xu et al., 2012) and obtaining data at low temporal and spatial scales (Pettorelli et al., 2005). The growing importance of spatial and temporal continuous data in these studies (Delbart et al., 2005) has made remote sensing increasingly relevant, as this approach allows for large-scale and frequent sampling (Zhang et al., 2003). Advances in geospatial technology and remote sensing will further increase the relevance of such methods to agroecosystems management and monitoring by raising productivity and reducing environmental degradation (Van Niel and McVicar, 2004).

Remote sensing has proved to be instrumental to the monitoring of rice agricultural production (Lopez-Sanchez et al., 2011; Gumma et al., 2014) and flooding (Moré et al. 2011; Son et al., 2013; Boschetti, 2014) at both regional and global scales. One of the first space borne multispectral sensors developed for rice monitoring is the Landsat Multispectral Scanner (MSS) (Ustin, 2004). Providing a spatial resolution of 30 m, Landsat images are frequently used in rice studies (Oguro et al. 2001; Báez-González et al., 2002, Moré et al. 2011; Li et al., 2012). Other sensors such as the NOAA Advanced Very High Resolution Radiometer (AVHRR) and SPOT-4 VEGETATION generate daily low spatial resolution images (1 km) (Xiao et al., 2002) and produce appropriate spectral bands that can be used in plant phenology studies. These sensors have been widely used

for rice development monitoring in many studies (Fang et al., 1998; Kamthonkiat et al. 2005; Singh et al. 2006).

Launched in 1999, Moderate Resolution Imaging Spectroradiometer (MODIS) includes advantageous features of both the AVHRR and Landsat. The 8-day composite MODIS data product provides medium spatial resolution images (500 m) of adequate temporal resolution and improved atmospheric correction (Vermote and Vermeulen, 1999). MODIS includes seven bands that are designed to detect water and vegetation, which allows to study plant phenology (Delbart et al. 2005, Sari et al., 2010, Xu et al. 2012) and flooding (Ordoyne et al., 2008).

The MODIS spectral index time series has been used in several studies for monitoring rice phenology and dynamics (Sakamoto et al., 2006; Motohka et al., 2009; Jacquin et al., 2010). Among spectral indices, the Normalized Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), which are based on photosynthetic activity, exhibit a good dynamic range and sensitivity for monitoring spatial and temporal variations in vegetation (Huete et al., 2002). The NDVI has been widely used in rice monitoring studies (Gumma et al., 2014). This index effectively detects heading dates (Boschetti et al., 2009; Wang et al., 2012) and shows sensitivity to soil wetness, making the tool suitable for monitoring irrigation start and padding (Motohka et al., 2009). EVI has also been used for rice crop monitoring and mapping (Xiao et al. 2005; Peng et al., 2011; Son et al., 2014). This index exhibits low sensitivity to vegetation canopy background variations and resists saturation in a dense canopy (Huete et al., 2002; Motohka et al., 2009). Thus, while EVI is more effective at avoiding saturation within a dense canopy, NDVI best detects soil condition changes (Motohka et al., 2009) while maintaining a suitable capacity to monitor rice phenology.

Spectral indices based on shortwave infrared bands have also been used to detect phenological events and rice hydroperiod (Xiao et al., 2002; Boschetti et al., 2014). The Normalized Difference Water Index (NDWI(1)), which combines information included in the SWIR1 and NIR, is sensitive to soil and vegetation water response (Gao, 1996). The tool has proved useful in identifying vegetation statuses (Fensholt and Sandholt, 2003) and flooding events (Ordoyne et al. 2008). Although this index was originally designed to detect vegetation water content, a number of works have also studied its effectiveness at monitoring surface water content (Boschetti et al., 2014). Additionally, NDWI(2), which combines SWIR2 and NIR bands, effectively detects significant increases in cropland surface water (Xiao et al. 2002) and monitors phenological stages (Delbart et al., 2005). Both of these capabilities (soil and vegetation water content detection) are essential to identify soil and crop water variations associated with rice phenology.

Other recent studies have demonstrated an interest in using new indices to characterize crop phenology and soil water content patterns (Das et al., 2013), as these indices can provide additional agricultural information that may be used to improve the results of other indices used separately. New approaches based on spectrum spectral shapes that combine angles formed by consecutive bands have been used successfully for this purpose in recent years (Palacios-Orueta et al., 2006). These new indices, referred to as Spectral Shape Indices (SSI), provide information of relationships between three consecutive bands, summarizing respective wavelength reflectance spectra. The Shortwave Angle Slope Index (SASI) (Khanna et al., 2007) in particular is based on the SWIR1 angle and is modified by including the slope between the NIR and SWIR2 reflectance. This index shows promising results in discriminating between land cover types and predicting soil and vegetation moisture content levels in laboratory and model simulated datasets. Das et al.

(2013) illustrated the utility of SASI in determining soil wetness and dryness through threshold values, and Palacios-Orueta et al. (2012) used a modification of SASI, AS1, to monitor cotton key phenological stages. All these attributes make SASI potentially useful for detecting rice cycle dynamics: given its proved sensitivity to soil moisture changes, it may more effectively identify rice phenology and hydroperiod characteristics.

The monitoring of phenological crop stages and dynamics using spectral indices is frequently based on the derivation of time series phenological metrics (Sakamoto et al., 2005; Zhang et al., 2012), normally from NDVI, EVI and NDWI indices. These phenological metrics typically include transition dates such as the heading date (Boschetti et al., 2009; Wang et al., 2012), plant emergence and harvesting (Boschetti et al., 2009; Wu et al., 2010) and have been used with varying degrees of success. Methodologies applied for phenological metrics determination vary from the use of threshold values to the identification of maximum and minimum values. These studies focus on determining one or more phenometrics from one index or from a combination of indices (Sakamoto et al., 2005; Leinenkugel et al., 2013; Chumkesornkulkit et al., 2013).

Statistical time series analyses of data from multispectral sensors provide information on dynamics of crop growing patterns. In particular, the autocorrelation function (ACF) (Box et al., 1994) enables to conduct a quantitative evaluation of the stability of temporal patterns in terms of seasonality and periodicity, providing useful information of underlying processes (Dornelas et al., 2013). When used for crop monitoring, the ACF reveals meaningful information on crop dynamics and has been used to detect variations in cropping patterns (Setiawan et al., 2014). Therefore, a statistical approach based on the use of ACF for the study of spectral index time series may generate relevant information on vegetation and water dynamics.

Although several methodologies have been developed to explore specific phenometrics in rice and to provide tools for rice mapping, no definitive approach is used to identify all phenological stages present in rice systems (Boschetti et al., 2009), including hydroperiod. The availability of optical information in VIS-NIR and SWIR regions makes it possible to propose an integrative approach based on the use of an optimal combination of indices for improving the assessment of rice agricultural practices, crop dynamics and flooding management. An assessment of different indices in rice growing areas with different flooding regimes would set the basis for developing a complete detection tool for phenological stages and agro-practices adapted for particular rice systems. In addition, this approach (i.e., phenometric) could be supplemented with information on general dynamics provided by temporal autocorrelation patterns.

The objective of this work was to assess the potential of different spectral indices for monitoring rice agricultural practices and hydroperiod dynamics by combining phenometric and statistical time series approaches. Four spectral indices were tested: the NDWI(1), NDWI(2) and SASI are based on the SWIR spectral region, and so they are related to water content, and the NDVI, based on photosynthetic activity, which is the most commonly used index in crop monitoring. This evaluation was focused on the study of their general dynamics and specific phenometrics. Based on the results obtained, a combination of indices was proposed. The analysis examined two rice-cropping areas that exhibit considerably different flooding regimes and which are governed under different management practices, thus resulting in different soil moisture and vegetation status dynamics.

The specific objectives of this study were:

- 1) To assess and compare the seasonal stability of vegetation and water dynamics in the two zones through a statistical analysis of index time series over a 12-year period
- 2) To analyze MODIS indices behaviors (including SSI) in relation to rice growth stage and flooding characteristics, as well as the capability for these indices to monitor hydroperiod and agro-practices patterns in areas governed under different flooding regimes.

3.2. Study areas and Rice Crop Cycle: Ebro Delta and Orellana

3.2.1 The Ebro Delta

The Ebro Delta, covering an area of 32,000 ha, is located along the north-eastern coast of the Iberian Peninsula (Fig. 3.1). The climate is Mediterranean, with an annual mean temperature of 18°C and an annual mean rainfall level of 556 mm. Croplands, protected wetlands and lagoons coexist in the area, and agricultural land, which is largely composed of rice fields, covers 21,500 ha. Rice paddies are flooded for nine months of the year to avoid salt level increases from the saline aquifer and to provide shelter and food for protected fauna. Rice field irrigation (flooding stage) roughly starts during the third week of April and involves complete flooding in two weeks. Water is driven by gravity through a network of irrigation canals and flows continuously into the rice fields. Drainage water is evacuated through surface drainage systems, managing field salinity and discharging the water into the sea and to surrounding lagoons.

Fig. 3.1. Study area: The Ebro delta, Catalonia (Spain).

The rice cycle lasts for between 120 and 140 days depending on the rice varieties involved and the interannual climatic fluctuations. Sowing occurs during the period between May 1st and May 15th. During the crop vegetative stage, which occurs between the sowing and heading date, significant structural development occurs due to leaf growth, and maximum biomass levels are reached at the heading date, which occurs roughly by late July. After the heading date, the reproductive stage begins, which is characterized by the development of rice panicles and a lack of vegetative growth. Over time, the crop wilts, and harvesting typically begins during the first week of September and is completed by the end of the month.

Rice fields are flooded again from the first week of October until mid-January in compliance with environmental measures agreed with farmers. Water levels during this environmental flooding period are lower than the typical 10 cm level maintained during the rice-flooding season, and these levels vary between fields. After the end of the environmental flooding stage, it takes nearly one month to drain the rice paddies. Depending on weather conditions, no water remains in the fields until the beginning of the next flooding season.

3.2.2 Orellana

The Orellana irrigated area is located close to the Guadiana River in the south-western region of the Iberian Peninsula (Fig. 3.2). The climate is Mediterranean with continental influences and scarce precipitation. Certain districts, including the 8,500 ha area studied in this work, are nearly completely covered with rice paddies, as rice crops are one of the most economically relevant resources in this zone. The hydroperiod roughly begins during the last week of April, although this period may be delayed until approximately May 15th due to inadequate weather conditions. It should be noted that the process is not simultaneous. Rather, some areas are flooded before others. The fields are maintained at a water level of 5 cm, with the exception of occasional variations due to specific agricultural management practices. Water applied to the fields percolates, discharges through a drainage network into tributary rivers, and finally flows into the Guadiana River.

The rice cycle in Orellana is similar to that of the Ebro Delta. However, as certain dates are shifted, the sowing date typically occurs one week later (roughly the second or third week of May). The heading date occurs during roughly the last week of July or beginning of August, and harvesting typically concludes by the first or second week of October, after which the fields remain bare and dry until the following rice season.

Fig. 3.2. Study area: Orellana, Extremadura (Spain).

For the cases studied, we have defined the following stages:

Flooding (F). Flooding is defined as the period of time between the beginning of field flooding and complete flooding.

Heading date (HD). The heading date is defined as the range of dates during which panicle emergence is present in most rice fields.

Harvest (H). The harvest coincides with the end of the hydroperiod in Orellana. This crop stage is determined as the last harvesting date according to field data and is characterized by higher levels of interannual variability due to climatic conditions.

End of Environmental Flooding (EEF). This event specifically applies to the Ebro Delta and is defined as the date at which rice fields are completely drained. The length considered for this stage is longer, as field drainage is highly influenced by management practices.

A crop calendar detailing rice-flooding periods in both study areas is included in Table 3.1.

Table 3.1. Crop calendar and flooding stages for rice in the Ebro Delta and Orellana.

3.3. Data sources

The MOD09A1 dataset, which consists of an 8-day MODIS composite grid-level product at 500-meter spatial resolution, was acquired for the period of 2001-2012. The longest time series available was used to obtain average values of indices that adequately reflected the general behavior of the two zones. This dataset of 552 images contains reflectance values for Bands 1-7 (450 nm (Blue), 555 nm (Green), 645 nm (Red), 860 nm (NIR), 1240 nm (SWIR1), 1640 nm (SWIR2) and 2130 nm (SWIR3)), quality control flags, observation dates and sensor zenith angles per pixel. MOD09A1 products for the study areas were downloaded from the MODIS website (<http://redhook.gsfc.nasa.gov/>) and re-projected using the MODIS re-projection tool (<http://edc.usgs.gov/programs/sddm/modisdist/>) to UTM zone 30. Quality flags were decoded using LDOPE.

Crop calendars and descriptions of agricultural and water management practices were provided by water user associations based in both zones. The two selected areas are primarily devoted to rice cultivation, although a number of fields in Orellana include other crops, resulting in mixed pixels. Water management practices differ between the Delta and Orellana, and some phenological dates vary due to climatic differences. Although agricultural management practices are analogous, crops times vary between farmers. Digital crop maps for the studied areas were provided by the “Confederación Hidrográfica del Guadiana” (Ministry of Agriculture), CEDEX (Ministry of Public Works) and by water user associations.

3.4. Methodology

3.4.1 Calculation of spectral indices

In this study, NDVI, SASI (Khanna et al. 2007), NDWI(1) and NDWI(2), which is also known as Land Surface Water Index (Xiao et al., 2005), were used. NDVI was selected for its performance in detecting the heading date (Wang et al., 2012) and as a reference for the rest of the indices. We also applied NDWI(1) and NDWI(2), which are sensitive to leaf water and soil moisture (Xiao et al. 2005), as well as SASI, which is a shape index developed to distinguish among dry soil, wet soil, dry vegetation and green vegetation (Khanna et al., 2007). The first three indices are normalized difference indices that utilize surface reflectance values from the red, NIR, SWIR1 and SWIR2 bands, as described in equations (3.1), (3.2) and (3.3):

$$NDVI = (\rho_{NIR} - \rho_{RED}) / (\rho_{NIR} + \rho_{RED}) \quad (3.1)$$

$$NDWI(1) = (\rho_{NIR} - \rho_{SWIR1}) / (\rho_{NIR} + \rho_{SWIR1}) \quad (3.2)$$

$$NDWI(2) = (\rho_{NIR} - \rho_{SWIR2}) / (\rho_{NIR} + \rho_{SWIR2}) \quad (3.3)$$

The last index listed is a spectral shape index (SSI), which is a variant of the SANI developed by Palacios-Orueta et al. (2006) and later modified by Khanna et al. (2007). SASI includes a combination of NIR, SWIR1 and SWIR2 MODIS bands and is based on the angle formed by the SWIR1 vertex with NIR and SWIR2 in the spectrum. The index explores the relationship between bands and coarsely emulates the behavior of this part of the spectrum. It is based on Whiting et al. (2004), which found a high correlation between the SWIR region and soil moisture. This index is defined by Khanna et al. (2007) as the product of the SWIR1 angle (β_{SWIR1} , Fig. 3) and the slope of line “c” that links reflectance (R) at NIR and SWIR2 vertices (Fig. 3.3). The equations for calculating SASI are described in (3.4), (3.5) and (3.6) below:

$$\beta_{SWIR1} = \cos^{-1}[(a^2 + b^2 - c^2) / (2 * a * b)] \quad (3.4)$$

$$Slope = (R_{SWIR2} - R_{NIR}) / d \quad (3.5)$$

$$SASI = \beta_{SWIR1} * Slope \quad (3.6)$$

Fig. 3.3. Relationship between angle β_{SWIR1} formed at SWIR1 and the slope of line c. Spectral values have been forced to coincide at SWIR1 to illustrate the relationship between angle and slope in SASI (adapted from Palacios-Orueta et al., 2006); a, b, c and d are referred to the Euclidean distances between the wavelength and reflectance at NIR (RNIR) and SWIR2 (RSWIR2).

In general terms, slope c is positive for dry soils and decreases for wet soils. Vegetation residue and dry vegetation hold a slope close to zero, and green vegetation generates negative values. The value of angle β_{SWIR1} , which is also referred to as AS1, is typically large for green vegetation and dry soils, and smaller for wet soils and dry vegetation. Thus, the product of the angle and slope is positive and large for dry soils, and negative and large for green vegetation. For dry matter, SASI is close to zero, as both the angle and the slope are small. In wet soils, the index is positive but small due to a decrease in β_{SWIR1} .

The time series for each reflectance band were compiled, and the indices were calculated for the whole study period using ENVI4.5.

Many rice phenological studies that use MODIS indices apply noise-filtering techniques to the data time-series (Boschetti et al. 2009; Son et al., 2014) due to abnormal values caused by certain atmospheric conditions (Chen et al., 2004). In this work, low quality pixel values were eliminated based on MODIS quality data bands, and cloud-contaminated pixels were removed based on the internal cloud algorithm flag of MOD09A1.005 500-meter Surface Reflectance Data State QA. Other outliers were identified as values falling outside the range of the mean plus/minus twice the standard deviation within a five-date period window. Missing data were replaced with the average of the previous and subsequent date values in the time series.

3.4.2 Data analysis

Statistical Time series analysis

The dynamics of indices of both study sites for the period 2001-2012 were first assessed by means of the autocorrelation function (ACF) of the time series. The ACF provides a measure for the correlation of a variable with itself at different time lags. As a mathematical tool, it identifies either repetitive patterns or the presence of periodic components in a time series, generating information that may be obscured by noise (Box et al., 1997).

The time series autocorrelation function (3.7) was implemented in IDL language. This function is composed by the sequence of autocorrelation coefficients r_k , until lag order k. For stationary processes, the ACF general equation is calculated from:

$$\hat{r}_k = \frac{\sum_{t=k+1}^N (y_t - \bar{y}) \cdot (y_{t-k} - \bar{y})}{\sum_{t=1}^N (y_t - \bar{y})^2} \quad (3.7)$$

Where $\hat{r}_k$ is the autocorrelation coefficient for lag k, y is the studied variable and $\bar{y}$ is the mean value of y.

The average ACF was calculated for each index to explore general rice crop dynamics. To assess the consistency of temporal patterns within each study area, spatial variability in index dynamics based on ACF values was evaluated by means of the Spectral Angle Mapper algorithm (SAM) (Kruse et al. 1993). The SAM is a tool that was originally implemented for mapping spectral similarity between image and reference spectra. In this model, a spectrum is considered a vector with a dimensionality equal to the number of bands. Thus, the difference in shape between the two spectra can be calculated as the “angular distance” between two vectors. In this work, the ACF was defined as an n-dimensional vector so that the difference in dynamics between two time series could be evaluated as the difference in shape between corresponding ACF values based on the angular distance between them. Therefore, small angle values indicate a high similarity in shape between ACFs and so, similar dynamics. This analysis was performed on a pixel scale so that the average ACF and angular distance between each pixel ACF could be calculated, and the pixels were classified into four categories, based on their similarities with average dynamics. A rice mask derived from digital crop maps was used in both zones. The results obtained were used to verify the soundness of using annual average index time series to represent general behaviors in each study site.

Seasonal behavior of spectral indices in Orellana and the Ebro Delta. Assessment of the performance in agro-practices and hydroperiod detection.

The spatial average of the average year for the four indices was calculated in each area. The resulting values were used to explore general index patterns and to characterize significant points that coincided with agro-practices data. Variations in index behaviors during transition dates and their sensitivity to variations in soil humidity, flooding regimes and management practices were also assessed. In this study, results were expressed in terms of the MD (MODIS Date) in reference

to each MODIS 8-day composite. For the average year, 46 MDs determined from calculations on 552 images from the 2001-2012 MODIS dataset were analyzed.

The relationship between MD, crop and agro-practices dates is described in Table 3.2. The term DOY represents the range of days of the year corresponding with the phenological stage or a specific agricultural practice, and MDOY (MODIS Date Of the Year) represents the range of days closest to the agricultural stage during which a MODIS image was obtained.

Rice phases	Ebro Delta				Orellana			
	Date	DOY	MDOY	MD	Date	DOY	MDOY	MD
Flooding (F)	Apr.15 th - May 1 st	105-121	105-128	14-16	Apr. 25 th - May 9 th	115-129	113-136	15-17
Heading date (HD)	Jul. 25 th - 30 th	206-211	201-216	26-27	Jul. 25 th – Aug. 5 th	206-217	201-216	26-27
Harvest (H)	Sept. 1 st - 30 th	244-273	249-280	32-35	Sept. 30 th – Oct. 8 th	273-281	273-288	35-36
End of the Env. Flooding (EEF)	Jan. 15 th -Feb. 15 th	15-46	17-48	3-6	-	-	-	-

Table 3.2. Hydroperiod, agricultural practices and crop phenological timing in Orellana and the Ebro Delta. The DOY is the range of days of the year corresponding to the date of the hydroperiod or crop stage. The MDOY is the range of days of the year that contains the MODIS image closest to the hydroperiod or crop stage. The MD is the MODIS 8-day composite of the series of 46 annual images. (-) denotes an absence of a particular event in the zone studied.

Annual average indices were used to assess the spatial consistency of significant points and differences in behavior between indices depending on agricultural practices, phenological stages and flooding regimes in each zone. A specific combination of indices adapted to different management practices and flooding conditions was proposed for assessing hydroperiod, agricultural practices and stages for rice.

Validation

The absolute and relative maxima and minima dates provided in the annual profiles of the four indices (average 2001-2012) on a pixel basis were identified and compared with the dates of key agro-practices, rice cycle dynamics and flooding events. The coincidence between the derived phenometric and agro-practices and crop stages in each study area was assessed based on the percentage of well-detected pixels for each index, phenometric and region. To account for management variability, a margin of error of one week for F and HD and two weeks for H and EEF before and after the dates provided was permitted. Ground reference information consisted of a range of dates during which rice stages occurred and main agricultural practices were accomplished (Table 3.2). This information was provided by farmers and was used for validation purposes. Though data were not specific for each year and were instead based on general date ranges, phenometrics were identified for 12-year average indices. The distribution of the occurrence date (MD) of maxima and minima in the average annual profile for each index and region was explored using histograms. The length of the time series and high autocorrelation

values at annual lags were used to corroborate the appropriateness of using the average year to represent the behavior of rice crop dynamics in each region.

A workflow diagram containing the main steps followed in the analysis performed is explained in figure 3.4.

Fig. 3.4. Workflow diagram illustrating the main steps followed in this study. The image processing steps (first, second and third boxes) are described in sections 3.4.1 and 3.4.2, and the rest of them in section 3.4.2.

3.5. Results

3.5.1 Time series analysis

For each index considered, the autocorrelation function (ACF) was calculated to assess vegetation and water dynamics. Rice fields were classified into four categories based on similarities in dynamics (shape of the ACF) to the average ACF for each study area using the SAM algorithm. Figures 3.5.a, 3.6.a, 3.7.a and 3.8.a show the average ACF values for each index and study area as well as the representative ACF for each category. Figures 3.5.b, 3.6.b, 3.7.b and 3.8.b show the

results of the SAM classification, which represents the spatial variability of different ACF types, and therefore the spatial variability of index dynamics.

NDVI ACF values presented significantly high positive values at 46 lags (one year) and significantly negative values at 23 lags (half a year) in the Delta (Fig. 3.5.a), denoting a stable, single, cyclical pattern. The rest of the time series (Fig. 3.5.a, 3.6.a, 3.7.a and 3.8.a) showed significantly positive ACF values at one-year lag but did not present significantly negative ACF values at the half-year mark. Instead, ACF values were higher at 23 lags than at 12 and 36 lags, suggesting the presence of a secondary cycle during the year.

The NDVI and SASI time series presented high correlation values at one-year lag (Fig. 3.5.a and 3.6.a) while NDWI(1) showed intermediate ACF values, with the lowest values found in Orellana (Fig. 3.6.a), which also showed the highest degree of spatial variability. The NDWI(2) values in the Ebro Delta exhibited correlation values at one-year lag in a similar manner as NDVI, whereas Orellana exhibited intermediate values (Fig. 3.7.a).

Autocorrelation values at lag 23 presented larger differences between categories in each study area than those at the one-year lag. Relevant differences in NDVI and SASI ACF average patterns were located at the borders of the study sites in both zones (Fig. 3.5.b and 3.8.b) and were most likely caused by mixed pixels. This effect was also present and more noticeable in NDWI(1) and NDWI(2) (Fig. 3.6.b and 3.7.b). Regardless, pixels exhibiting this dynamic were few, relative to the rest of the pixels. NDWI(1) ACF values at 23 lags in Orellana were close to 0 and exhibited considerable spatial variability, although the spatial distribution presented consistent patterns (Fig. 3.6.b). In the Delta, the NDWI(1) ACF showed spatially consistent positive values that were higher in the eastern region close to the river mouth and coastline. A similar spatial pattern was showed by NDWI(2) (Fig. 3.7.b), which presented lower ACF values.

Fig. 3.5. Average NDVI ACF and variations of NDVI ACF (a) in the Ebro Delta (above) and Orellana (below). Spatial differences detected (b).

Fig. 3.6. Average NDWI(1) ACF and variations of NDWI(1) ACF (a) in the Ebro Delta (above) and Orellana (below). Spatial differences detected (b).

Fig. 3.7. Average NDWI(2) ACF and variations of NDWI(2) ACF (a) in the Ebro Delta (above) and Orellana (below). Spatial differences detected (b).

Fig. 3.8. Average SASI ACF and variations of SASI ACF (a) in the Ebro Delta (above) and Orellana (below). Spatial differences detected (b).

3.5.2 Seasonal behavior of spectral indices

The seasonal behavior of indices and the identification of key agricultural practices and phenological stages for each study area (Table 3.2) were determined based on the average year profile.

The average time series for both areas is showed in Fig. 3.9.a, b, c and d to complement information showed in index annual profiles. Figures 3.10.a, b, c and d show the index annual profiles for Orellana and the Delta. General flooding and agricultural dates provided by farmers (Table 3.2), (i.e., flooding (F), heading date (HD), harvest (H) and the end of environmental flooding (EEF) are also annotated.

Fig. 3.9. Average NDVI (a), NDWI(1) (b), NDWI(2) (c) and SASI (d) time series (2001-2012) for the Ebro Delta and Orellana.

The NDVI presented similar patterns during the growing season (Fig. 3.10.a) in both areas, and differences were noticeable throughout the non-growing period (from the beginning of October to the beginning of May), with values in the Delta being consistently lower than those in Orellana. In both areas, minimum values occurred at the beginning of the flooding stage (April 15th-25th to May 1st-9th), while maximum values appeared close to the heading date.

Fig. 3.10. Average annual profile of NDVI (a), NDWI (1) (b), NDWI (2) (c) and SASI (d) (2001-2012) for the Ebro Delta and Orellana.

The NDWI(1) and NDWI(2) profiles (Fig. 3.10.b, c) showed two major local minima at the beginning and end of the rice flooding season (beginning of April and beginning of October). Both indices showed a sharp increase in coincidence with rice flooding in both areas (April 15th-25th) and at the beginning of environmental flooding in the Ebro Delta (first week of October). The opposite trend was observed after fields were drained before harvest in both areas (from roughly September 1st to 30th-October 8th) and at the end of environmental flooding in the Delta (from January 15th to February 15th), with a relative minimum occurring at the end of the draining process.

The SASI (Fig. 3.10.d) showed similar shape and value characteristics in both study areas during the growing period, and differences were noticeable in the Delta during the environmental flooding

stage (October 1st-January 15th). In both areas, an absolute maximum occurred at the beginning of the rice flooding stage (April 15th-25th). Minimum values in both sites at the end of July occurred close to the crop heading date, while a relative maximum occurred near the end of the harvest. This maximum was less noticeable in Orellana than in the Delta and appeared after a two-week delay according to field data. SASI trends also showed a relative minimum before the end of the environmental flooding period.

Table 3.3 shows identified singular points that may be related to specific dates of agricultural practices provided by farmers.

	Flooding (F)		Heading Date (HD)		Harvesting (H)		End Env. Flooding (EEF)
	Delta	Orellana	Delta	Orellana	Delta	Orellana	Delta
NDVI	Abs. minimum		Abs. maximum				
	DOY: 121-128	DOY: 121-128	DOY: 209-216	DOY: 209-216			
NDWI(1)	Rel. maximum				Rel. minimum		Rel. minimum
	DOY: 137-144	DOY: 145-152			DOY: 273-280	DOY: 281-288	DOY: 41-49
NDWI(2)			Abs. maximum		Rel. minimum		
			DOY: 209-216	DOY: 209-216	DOY: 273-280	DOY: 297-304	
SASI	Abs. maximum		Abs. minimum		Rel. maximum		Rel. minimum
	DOY: 97-104	DOY: 113-120	DOY: 209-216	DOY: 217-224	DOY: 273-280	DOY: 297-304	DOY: 9-16

Table 3.3. Singular points found that are coincident with agro-practices and rice stages of Orellana and the Ebro Delta. The DOY refers to the day of the year in relation to agricultural practices and crop stages.

3.5.3 Assessment of agricultural practices and hydroperiod detection performance

Key singular points identified on the average annual profiles (Table 3.3) were also determined on a pixel scale for the average year in both study areas and then compared with dates provided by local farmers. Table 3.4 shows the percentage of pixels in which a singular point was detected within the range of occurrence dates for each stage based on a margin of error as described in section 3.2.3.

	Flooding (F)		Heading Date (HD)		Harvesting (H)		End Env. Flooding (EEF)	
	Delta	Orellana	Delta	Orellana	Delta	Orellana	Delta (B)	Delta (E)
NDVI	83.8	85.3	96.8	90.4	–	–	–	–
NDWI(1)	23.9	14.4	–	–	91.0	51.4		80.0
NDWI(2)	–	–	83.8	76.6	93.3	39.0	–	–
SASI	38.1	89.8	93.6	83.1	90.3	60.5	69.0	–

Table 3.4. Percentage of pixels detected in coincidence with agricultural practices and crop calendar dates ± 1 week for F and HD ± 2 weeks for H and EEF. (-) Indicates non-assessed indices; (B) refers to the start of field drainage, and (E) refers to the end of the drainage process.

Figures 3.11, 3.12, 3.13 and 3.14 show histograms for these singular points; only those that could be related to a specific rice or flooding stage are represented. Values are presented as a percentage of the total number of pixels in each study area.

Approximately 84% and 85% of the Delta and Orellana NDVI profiles, respectively, exhibited a minimum within the range of flooding occurrence dates (Table 3.4). Ninety percent of the Orellana SASI pixels reached a maximum during this period of the year with a narrow distribution (Fig. 3.11.b). However, coincidence was much lower in the Delta.

Fig. 3.11. Frequency distribution of singular points for NDVI, SASI and NDWI(1) close to F in the Ebro Delta (a) and Orellana (b) on a per-pixel basis.

Maximum values detected in NDVI within the range of dates defined for the heading date were close to 97% and 90% in the Delta and Orellana, respectively (Table 3.4). The SASI showed a

minimum of 94% of pixels in the Delta for this period while in Orellana this ratio dropped to 83%. Although in both indices the histograms of the maximum point in SASI were narrow, in Orellana the maximum appeared after an 8-day delay relative to NDVI data (Fig. 3.12.b).

Fig. 3.12. Frequency distribution of singular points in NDVI, SASI and NDWI(2) close to HD in the Ebro Delta (a) and Orellana (b) on a per-pixel basis.

Minimum values in NDWI(2) and NDWI(1) that were concurrent with the harvest period were detected in 93% and 91% of the pixels for the Delta (Table 3.4), while in Orellana this coincidence was observed in only 39% and 54% of the pixels. Over this range of dates, the SASI index showed a maximum in 90% and 60% of the pixels in the Delta and Orellana, respectively. In the Delta, NDWI(1), NDWI(2) and SASI singular points were located within a narrow interval of dates (Fig. 3.13.a), whereas points in Orellana were more broadly distributed. Additionally, the minimum value in NDWI(2) was delayed by two weeks relative to points detected by NDWI(1) and SASI (Fig. 3.13.b).

Fig. 3.13. Frequency distribution of singular points in NDWI(1), NDWI(2) and SASI close to H in the Ebro Delta (a) and Orellana (b) on a per-pixel basis.

The NDWI(1) and SASI presented minimum values in 80% and 69% of the pixels within the range of dates defined as the end of the environmental flooding period in the Delta (Table 3.4). The histograms showed that the majority of points were situated within a three-week interval in both indices (Fig. 3.14); however, the SASI minimum values appeared three weeks before those of NDWI(1), and a notable number of pixels presented a six-week delay relative to the main group.

Fig. 3.14. Frequency distribution of singular points in SASI and NDWI(1) close to EEF in the Ebro Delta on a per-pixel basis.

Figures 3.15.a, b, c and d show the combination of indices that achieved the best results for the Delta and Orellana according to field data (also annotated) for a single pixel (Fig. 3.15.a and b) and for the average year (Fig. 3.15.c and d).

Fig. 3.15. Single-pixel and average NDVI, NDWI(1), NDWI(2) and SASI profiles for the Ebro Delta (a, c) and Orellana (b, d). Singular points identified and field data provided by local farmers are also annotated.

3.6. Discussion

In this study, the behaviors of four MODIS indices for assessing the agricultural practices (flooding and harvesting period), rice heading stage occurrence and hydroperiod characteristics in rice were analyzed in the study areas. The effectiveness of these indices in assessing soil surface statuses during transition periods in relation to the flooding regime was of special interest. The results obtained through the exploration of the ACF and its annual dynamics proved the soundness of evaluating agricultural practices and rice crop dynamics based on the analysis of spectral indices for a reference year, computed as the multi-year average for the studied period. The occurrence of two intra-annual cycles in the ACF of some indices denoted the existence of two maxima or two minima per year. Thus, the methodology for assessing index performance was based on the detection of minimum and maximum points as phenometrics of average indices for the period (2001-2012). The points identified were compared with average dates of agricultural practices provided by local farmers to test the consistency between indices and field data. The detection of phenometrics worked more effectively overall for the Delta than for Orellana, most likely due to

the homogeneity of the Delta, both with respect to land cover and to agricultural management practices.

The NDVI ACF presented the highest values at one-year lag, illustrating the consistency of annual patterns throughout the 2001-2012 period (Fig. 3.5.a). Spatial variability was found to be low, demonstrating the representativeness of the average profile for identifying phenometrics. The NDVI ACF of the Delta was the only one denoting a single intra-annual cycle (Fig. 3.5.a), with negative AC values at a 23 lag (half a year). This behavior indicated that NDVI distinguished active crop stages from non-photosynthetic stages, though it did not capture variability during the non-growing season (i.e., bare soil vs. environmental flooding). In contrast, the NDVI ACF revealed a double intra-annual cycle in Orellana (Fig. 3.5.a), suggesting variability during the non-growing period, which may be attributed to the presence of weeds in the fields.

The NDVI average profile presented a maximum close to the heading date (Fig. 3.10.a) and coincident with the maximum LAI (Boschetti et al., 2009, Wang et al., 2012). The lack of noise in this index and the consistency of the maximum resulted in high levels of agreement with field data (Table 3.4). Low autumn-winter NDVI values in the Delta occurred due to the combined effect of vegetation residue and flooded soils, and these values decreased slightly after the fields were drained. After this, the index reached a distinct local minimum prior to crop emergence that matched the subsequent flooding stage (Fig. 3.10.a). The occurrence of this minimum within the range of dates provided was observed in 84% of the pixels (Table 3.4), accurately denoting a transition from bare flooded soil to rice emergence. This minimum was also present in Orellana (Fig. 3.10.a), where similar results were achieved (Table 3.4). For this area, the existence of a SASI maximum that coincided with the start of the hydroperiod (Fig. 3.10.d) was more accurately detected (Fig. 3.11.b). The consistency of this maximum is most likely attributed to the response of this index to dryness in bare soils prior to flooding. SASI was expected to reach higher values for bare, dry soil stages and lower values for wet and flooded soils (Khanna et al., 2007). In fact, other studies have proposed the use of threshold values in SASI to track soil wetness (Das et al., 2013). High SASI ACF values and the existence of a distinct, biannual pattern in Orellana (Fig. 3.8.a) were in agreement with the presence of this maximum. In the Delta, on the other hand, soils were not completely dry by the beginning of the hydroperiod due to environmental flooding. This reduced the contrast between soils before and after flooding, resulting in a less significant SASI maximum (Fig. 3.10.d). Differences in soil moisture dynamics between the study areas were most likely the cause of the different results in the detection of the flooding period by SASI.

The performance of indices in identifying the harvest showed consistently better results in the Delta than in Orellana (Table 3.4). This is likely attributable to differences in management practices between the two areas. In the Delta, the harvest process resulted in a transition from wilting vegetation to flooded soils that produced a more distinct minimum in NDWI(1) and NDWI(2) and a maximum in SASI (Fig. 3.10.b, c and d). In Orellana, the transition from wilting

vegetation to bare dry soil was not as easily identifiable, especially in NDWI(2) (Fig. 3.13.b). In this area, the SASI relative maximum was correctly identified in a higher percentage of pixels than the minima in NDWI(1) and NDWI(2) (Table 3.4). These findings complement the results of other researchers who found that SASI effectively identifies wilting vegetation in both wet and dry soil (Khanna et al., 2007). The existence and consistency of these points in NDWI(1), NDWI(2) and SASI was in agreement with the double ACF pattern identified (Fig. 3.6.a, 3.7.a, 3.8.a), denoting the occurrence of distinct dynamics throughout the non-growing season.

During environmental flooding, both NDWI(2) and NDWI(1) exhibited higher values in the Delta than in Orellana (Fig. 3.10.b, c) due to the presence of water in the fields. The SASI index also detected these differences in water management, showing consistently lower values in the Delta (Fig. 3.10.d). Khanna et al. (2007) showed that SASI detects higher values in dry soils, and this is in agreement with the results obtained. This finding highlights the importance of SWIR bands for rice monitoring during the non-photosynthetic period.

Both SASI and NDWI(1) provided relevant information on the beginning and end of the drying process following the hydroperiod in the Delta. In 69% of the pixels, SASI presented a minimum in coincidence with the beginning of the drainage process (Fig. 3.10.d), illustrating an increasing trend as water levels decreased. On the other hand, NDWI(1) showed a minimum value at the end of the field drainage period (Fig. 3.10.b). After this point, the index recorded stable values. This finding is consistent with other works that discuss the response of this index to soil and vegetation water content (Gao, 1996). The secondary cycle at lag 23 in the NDWI(1) ACF (Fig. 3.6) is most likely attributable to its regular response to environmental flooding, allowing for highly accurate means of identifying this stage (Table 3.4). The combination of results obtained from the two indices may provide an estimation of field drainage period length at the end of the hydroperiod in the Delta (Fig. 3.14), improving the robustness of its characterization.

Our results showed that the dates of agricultural practices, heading stages and hydroperiod in rice may be identified by combining information derived from the four indices studied. Index behaviors in rice paddies in which soils were dry from harvesting until the following rice season (i.e., Orellana) differed from those in rice paddies in which flooding occurred after harvesting (i.e., Delta). In addition, each index exhibited different capabilities during different periods of the year. These results suggest that it is appropriate to use different combinations of indices to detect hydroperiod and agricultural practices in regions with different soil moisture dynamics throughout the year (Fig. 3.16).

The NDVI relative minimum may be used to detect flooding stages in sites that are flooded or in which soils are kept moist for the majority of the year. On the other hand, the SASI maximum would better suit fields with shorter hydroperiods and dry soils before the flooding stage. The maximum of NDVI could be used to detect heading date in any instance, and the minimum of

SASI is the second best measure for this purpose. The relative minimum of NDWI(2) may be applied to detect harvesting in sites that include a second flooding event after harvesting, while the SASI maximum shows stronger results for transitions between vegetation wilting and soil drying than the rest of the indices. The minimum of SASI may be used to detect the start of the drainage process at the end of the environmental flooding period, and the NDWI(1) minimum can be applied to detect the end of the drainage process.

Though in this study rice fields were identified using a rice mask, other methodologies may be used to determine rice areas. Since rice fields are not typically managed under crop rotation schemes, once the rice fields are identified the proposed strategy could be used in a robust manner for areas under similar management practices. Our results, which showed significant stability in rice fields in the two study areas throughout the study period, support this hypothesis. Thus, a method for confirming crop permanence every year may be more appropriate than a mapping procedure. In this sense, the autocorrelation approach by means of the ACF provides essential information on the recurrence of similar patterns each year.

Figures 3.16.a and 3.16.b show two schematic diagrams of the specific agricultural practices, crop stages and hydroperiod characteristics that could be identified by each of the indices tested in rice systems similar to Orellana and the Delta respectively. A specific combination of an index and a metric could be used to detect each stage.

Fig. 3.16. Schematic diagram depicting the specific agricultural practices, crop stages and hydroperiod characteristics that could be identified by each index in rice systems similar to Orellana (a) and the Delta (b).

This work presented the results of the characterization and assessment of different indices behavior and dynamics in rice systems. The spatial and temporal stability shown within each area made it possible to evaluate the capability of the indices analyzed based on the average year; however, to develop an agro-monitoring tool, assessments should be applied to each specific year. In such cases, smoothing and validation procedures would be necessary.

3.7. Conclusions

In this study, indices exhibiting variable detection capacities depending on flooding regimes and management practices in different zones were identified. NDVI, NDWI(1) and NDWI(2) most effectively identified agricultural practices and hydroperiod characteristics in the Delta while NDVI and SASI performed better when applied to Orellana due to differences in soil moisture dynamics. Based on the results obtained, we have proposed a specific combination of indices for assessing rice flooding events, some crop stages and agricultural practices (Fig. 16) in relation to different management practices.

The main findings of this work are:

- Although NDVI effectively identified rice dynamics over the growing period, it was not able to assess the variability out of the growing season, which were more accurately assessed by NDWI(1), NDWI(2) and SASI.
- The existence of a significant response to flooding events showed in NDWI(1), NDWI(2) and SASI illustrates the importance of SWIR spectral wavelengths to detect flooded and wet soils. Specifically, SASI exhibited a strong capacity to identify changes in soil water content, and especially at the beginning of the drainage period, which may encourage its use in wetland monitoring studies.
- A considerable consistency between the time series statistical analysis (i.e. ACF) and phenometric approaches was showed by the coincidence between distinct phenometrics and the double cycle pattern of the ACF. The ACF provided useful information for assessing spectral indices dynamics and patterns related to vegetation and flooding dynamics in rice. The analysis performed identified the homogeneity in the pattern of the indices between years for the time series and the differences in the annual cycles due to changes in vegetation and flooding dynamics.

The generalization of these results to other rice regions will depend on specific water management practices in each area. The proposed combination for the Ebro Delta may most likely be applied to areas characterized by a double rice cycle, which may present similar transitional characteristics across agricultural events of dry soil, wet soil, green vegetation and wilting vegetation. The combination of indices that works more effectively in Orellana may be used in areas characterized by a single rice cycle, in which soil remains dry until the next rice season. The application of this approach as a monitoring tool should rely on the use of complete time series and specific validation.

This approach may improve rice phenometric detection practices in many countries where crop calendars and water management monitoring resources are not accessible. The results obtained may be used to establish water management policies and for developing methane emissions and vegetation dynamics studies. The results showed that while rice crops exhibit a number of common patterns, management practices can differ, resulting in different dynamics that necessitate different approaches to rice crop monitoring from Remote Sensing.

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CHAPTER 4

Evaluation of actual evapotranspiration in rice ecosystems
based on remote sensing data

Chapter 4. Evaluation of actual evapotranspiration in rice ecosystems based on remote sensing data.

4.1. Introduction

Rice ecosystems are key contributors to the reduction of hunger and poverty (Nguyen, 2002), as well as important aquatic ecosystems hosting a large variety of wildlife (FAO 2013). Rice is cultivated in more than 159 million of ha worldwide (IGC, 2016) and under different climates, with huge extensions planted in coastal areas, such as the Mekong River Delta, the Nile Delta and coastal regions of India or Thailand. Rice fields are typically flooded during the rice cycle, and in some cases they are also flooded out of the rice growing season to host protected fauna (Martínez & Gilabert, M. A, 2009; Torbick et al., 2011) or fisheries (Fernando, 1993), implying the use of large amounts of water. Due to the presence of the free water layer and wet soil during long periods of the year the amount of evapotranspiration (ET) in rice fields exceed that in other crops, becoming a critical component in the estimation of the hydrological cycle in many parts of the world. Consequently, rice fields are not only the main providers of staple food in the world, but also one of the biggest water user (Hundertmark & Facon, 2003), with relevant effects on greenhouse gas emission (Meijide et al., 2017). However, ET remains as one of the most challenging hydrological flux to estimate particularly at regional or global scales in the assessment of water resources (Liou & Kar, 2014). In a context of rising rice demand and increasing water scarcity (Bouman et al., 2007), the provision of information about water usage in rice paddies is becoming a major concern worldwide. Thus, improving the estimation of ET (or latent heat flux, λE , if expressed in terms of energy balance) and their temporal and spatial variations will be essential to improve water management planning and monitoring (Lee et al., 2004; Chemin and Honda, 2006).

In the last years, many works have addressed the study of λE in rice areas (Chemin & Honda, 2006; Chávez et al., 2008; Facchi et al., 2013). The measurement or estimation of λE in flooded ecosystems such as rice paddies present many challenges: intra-annual variations in surface cover, the possible effect of air advection and the quantification of water evaporation beneath the canopy among others (Drexler et al., 2004; Yan et al., 2012). Additionally, λE is difficult to measure and predict, particularly at large spatial scales (Turner, 1989). Due to these circumstances, estimates of λE in flooded ecosystems sometimes are only referred to certain periods of the year or contain certain degrees of error (Drexler et al., 2004; Carlson et al., 2014), and consequently more comprehensive approaches are still needed.

In general, there is no universally accurate model or measurement methodology to estimate λE . Instead, each method has advantages and disadvantages based on cost, assumptions and data requirements among others (Drexler et al., 2004). Regarding the methods based on direct measurement, lysimeter devices have been used in some local studies in rice (Abdullahi et al., 2013; Maina et al., 2014). More recently, micrometeorological methods, and especially those based on the Eddy Covariance (EC) techniques, have demonstrated their accuracy and good results in rice fields (Alberto et al., 2011; Baldocchi et al., 2016; Wang et al., 2017). Additionally, EC

techniques do not affect the surrounding environment and are representative of larger surface areas (Facchi et al., 2013). However field measurements are generally expensive and restricted to local research works rather than being used at farm level or in regional studies, and are commonly applied for validation purposes (Facchi et al., 2013).

Other methodologies rely on estimation methods, allowing for longer and more extensive studies. Some aspects such as data availability, the intended use, and the time scale must be considered before selecting the model (Shih et al., 1983). The Penman-Monteith (PM) equation and the Priestley Taylor (PT) model, both based on a sound analytical basis, are the models presenting better results in flooded ecosystems such as rice fields (Lee et al., 2004; Drexler et al., 2004; Sun & Song, 2008;). The use of these models, in combination with remote sensing data, allows to obtain reliable estimates at large spatial and temporal scales. Although PM is more theoretically accurate, it requires numerous parameters and is limited by the lack of meteorological data (Lee et al., 2004; Fisher et al., 2008). On the other hand the PT model presents the advantage of simplicity and fewer input parameters required to estimate λE , allowing for a more extensive use. The use of the PT model in combination with remote sensing (RS) data potentially obtain good quality λE estimates, even in areas lacking specific meteorological inputs (García et al., 2013).

Remote sensing provides the opportunity to monitor and map rice ecosystems over large areas at repeated time intervals, allowing the study of variations in ecological variables in time and space (Kuenzer & Knauer, 2013). Particularly, the MODerate Resolution Imaging Spectroradiometer sensor (MODIS) includes advantageous features such as a thermal infrared band to retrieve air temperature and humidity, crucial in λE estimation. In the last years, the combined use of RS vegetation products and meteorological datasets as inputs of PT or PM equations has allowed to obtain regional estimates of λE (Mu et al., 2007). Among the methods integrating models and RS data, those based on surface energy balance and particularly two sources-models have become increasingly acknowledged (Yao et al., 2010; Colaizzi et al., 2012; Wang & Yamanaka, 2014). These models are based on the partition of energy into soil and canopy components. Accordingly, sensible and latent heat fluxes are considered to be transferred to the atmosphere from both components. The main advantage of these models is that they do not need precise atmospheric corrections, emissivity estimations and high accuracy in sensor calibration (Liou & Kar, 2014). However, the unavailability of specific data such as wind speed and soil moisture data in most regions of the world (De Bruin & Stricker, 2000) usually restrict their application. Fisher et al (2008), proposed a two-source model to evaluate λE at the global scale overcoming the lack of field data by combining RS information, Eddy Covariance data from the global network FLUXNET and the PT method. The Priestley Taylor- Jet Propulsion laboratory model developed (PT-JPL) was based in the use of plant physiological constraints and soil constraints to reduce potential to actual λE . This approach did not need on site calibration and performed well in different ecosystems and climate regimes. However, λE estimates were obtained at monthly temporal resolution, being necessary to improve this scale for obtaining adequate results in regional and local studies. This model was later modified by García et al., 2013, using MODIS RS datasets with the aim of adapting the model to obtain daily estimates. Additionally, a new formulation for the soil moisture constraint, based on soil thermal inertia (Verstraeten et al., 2006b)

was introduced. This alternative soil constraint allows for a more extensive use of the PT-JPL model, as no field calibration or water vapor deficit estimates are required. The results were validated with EC data specifically from drylands, obtaining promising results in the cases studied. This approach shows a strong potential to be applied in regional and long term studies in rice ecosystems, combining simplicity in inputs yet a physically sound development.

However, the particularities present in flooded ecosystems require specific modifications that consider intra annual strong variations in the soil water layer and the evaporation beneath the canopy, which have an important effect in global evaporation rates (Yan et al., 2012). There are only few studies based on a combination of RS data and λE models to estimate λE in rice fields (Chemin and Honda, 2006; Narongrit & Chankao, 2009; Lal et al., 2012) yet none of them has explored the potential of two source models in rice ecosystems. The use of this model would allow the consideration of soil flooding inter annual variations while maintaining simplicity and low dependence on external parameters. Thus, a physically sound model such as PT-JPL offers a promising perspective for its use in the estimation of λE in rice ecosystems and their spatial variation. Additionally, the use of MODIS time series data would allow the study of temporal patterns and periodicity in λE estimates, revealing meaningful information of ecosystem dynamics.

This study was aimed to test and adjust the PT-JPL daily to obtain estimates of λE in flooded ecosystems such as rice fields with low requirements of in situ data, in order to be feasible in locations with a limited availability of field data. The model performance was compared with Eddy Covariance field measurements from a FLUXNET tower placed in a coastal rice field in the Mediterranean Region (the Albufera, Spain). After validation the model was also applied in a similar rice ecosystem in the Ebro Delta (Spain).

The main objective of this work was to evaluate the PT-JPL daily, as formulated by Garcia et al., 2013, in rice ecosystems and introduce a modification accounting for the variable soil conditions present in flooded ecosystems.

The specific objectives of this study were:

- 3) To assess the importance of the intermittent flooding in the energy balance in order to adjust the daily version of PT-JPL model to flooded ecosystems, such as rice fields.
- 4) To assess the λE estimates from the daily version of PT-JPL model adjusted to rice ecosystems.
- 5) To analyze the behaviour of λE time series in two coastal rice paddies in the Mediterranean Region.

4.2. Study sites and data

4.2.1 Study sites

The Albufera Natural Park

The Albufera Natural Park, located in the eastern coast of Spain (Fig. 4.1) is a 21000 ha wetland ecosystem, including approximately 14500 ha of rice fields. The climate is Mediterranean, with an annual mean temperature of 18° and a dry summer. The precipitation is scarce, usually between 400-500mm, and mostly concentrated in autumn and spring. The rice cycle starts with the flooding of the fields the first week of May. Rice is sown between the 10th- 15th of May and plant emergence begins typically at the end of the month. The fields are covered by a green canopy between June and July and the harvesting takes place in September, after draining the fields. In the following weeks the rice fields are flooded again in compliance of environmental regulations. This winter flooding keeps an open water table until February. After that, the fields are drained and they are completely dry at the end of March.

Fig. 4.1. Study area: The Albufera Natural Park, Valencia (Spain).

The Ebro Delta

The Ebro Delta is a coastal region located along the north-east of Spain (Fig.4.2). The climate is similar to that of the Albufera, Mediterranean with an annual mean rainfall level of 556 mm. The total area is 32000 ha and is largely composed of rice fields, which cover 21500 ha, coexisting with protected wetlands and lagoons. Rice paddies are flooded during most of the year to prevent salinization due to the existence of a saline aquifer and also to provide an adequate environment

for the protected fauna. The flooding of the fields starts during the third week of April, following a strict schedule for having the entire Delta flooded in two weeks. Water is delivered through a network of irrigation canals and flows continuously into the rice paddies.

Fig. 4.2. Study area: The Ebro delta, Catalonia (Spain).

The rice is usually sown the first or second week of May, after the flooding of the fields. Plant emergence starts at the end of the month and maximum biomass levels are reached at the heading date, normally by late July. The next phenological phase, the reproductive stage, produces the development of rice panicles while the vegetative growth ceases completely. The harvest takes place typically the two first weeks of September, and is followed by a new flooding period starting the first week of October. This environmental winter flooding keeps water levels lower than the usual 10 cm during the rice cycle period. The winter flooding period last until the end of January and nearly one months is needed to completely drain the paddy fields. After that, the fields remain bare and dry until the beginning of the rice cycle in late April.

4.2.2 Data sources

Several MODIS products were acquired for the period 2010-2012 and downloaded from the MODIS website (<http://redhook.gsfc.nasa.gov/>). The time series selected was considered long enough to study evapotranspiration dynamics in this ecosystem.

Land surface temperature, emissivity and satellite time passing were obtained from MOD11A1 and MYD11A1. These two products consist of a daily-basis dataset at 1000-meter spatial resolution from Terra and Aqua satellites. Additionally, the Leaf Area Index (LAI) and the fraction of absorbed photosynthetically active radiation (f_{APAR}) were obtained from MOD15A2, an 8-day composite product at 1000-meter spatial resolution. The MCD43B3 16-day composite and the MOD13A2 8-days composite, both at 1000-meter spatial resolution, were also required to obtain the broadband surface albedo (α) and NDVI data respectively.

The flux tower in El Saler (the Albufera Natural Park, Spain), included in the FLUXNET initiative, provided validation datasets for the Albufera in the period studied, as well as meteorological information, water level and water temperature data. Site specific information regarding instrumentation and data handling is available at their web site. Agricultural information of crop calendars and water management practices was kindly provided by water user associations and several agricultural publications.

Meteorological data for the Ebro Delta were provided by the “Agencia Española de meteorología, AEMET” (Ministry of Agriculture). Water temperature in the fields and channels were obtained from automatic water quality stations of the “Confederación Hidrográfica del Ebro” (Ministry of Agriculture). Water level estimation from the rice fields, together with crop calendars were provided by water user associations. Digital crop maps for the studied areas were provided by CEDEX (Ministry of Public Works) and by water user associations.

The two cases studied are almost identical ecosystems: coastal rice paddies close to wetlands, under Mediterranean climate conditions and flooded for most of the year, combining the rice flooding period and the environmental winter flooding period.

4.3. Methodology

4.3.1 Model description

The model applied in this work, known as PT-JPL-daily, is based on the algorithm proposed in Fisher et al. (2008) and modified by Garcia et al. (2013). The model has been adjusted to variable flooding conditions in rice ecosystems, introducing the water storage term (Sw) during the flooding season.

In this study, actual evapotranspiration is estimated in energy terms as latent heat flux (λE), and computed as the sum of soil (λE_s) and canopy (λE_c) (Eq. 4.1). Potential evapotranspiration of soil (λE_{ps}) and canopy (λE_{pc}) are reduced to actual evapotranspiration based on plant physiological status and soil moisture constraints (Fisher et al., 2008). The calculation of potential evapotranspiration (λE_p) is based on the Priestley Taylor (1972) equation.

$$\lambda E = \lambda E_s + \lambda E_c \quad (4.1)$$

Plant physiological constraints are: (1) green canopy fraction (f_g), plant moisture (f_m) and plant temperature (f_T) (Eq. 4.2).

$$\lambda E_c = f_g f_m f_T \lambda E_{pc} \quad (4.2)$$

The green canopy fraction (f_g) reduces the evapotranspiration considering only the part of the canopy that is actively transpiring. This parameter is calculated as the ratio between intercepted photosynthetic active radiation (based on NDVI) and absorbed photosynthetic active radiation (f_{APAR}), as showed in Table 4.1. The estimates of NDVI and f_{APAR} are derived from MOD13A2 and MOD15A2 MODIS products respectively.

The plant moisture constraint (f_m) is formulated as the decrease in light absorptance in relation with the maximum ($f_{APAR}/f_{APARMax}$) and accounts for the reduction in plant absorptance due to moisture stress (Fisher et al., 2008) (Table 4.1).

The plant temperature constraint (f_T) is based on the reduction in photosynthetic efficiency when vegetation grows at temperatures out of their optimum temperature range (Table 4.1). It depends on the daily average air temperature T_a (°C) and the optimum air temperature for plant growth T_{opt} (°C). This last parameter has been fixed in 25°C, as described in Garcia et al. (2013).

	Variable	Description	Equation	Reference
Biophysical constraints	f_g	Green canopy fraction	$f_g = f_{APAR}/f_{IPAR}$	Fisher et al. 2008
	f_T	Plant temperature constraint	$f_T = 1.1884 \cdot [1 + e^{0.2 \cdot (T_{opt} - 10 - T_{am})}]^{-1} \cdot [1 + e^{0.3 \cdot (-T_{opt} - 10 - T_{am})}]^{-1}$	Fisher et al. 2008
	f_M	Plant moisture constraint	$f_M = \frac{f_{APAR}}{f_{APARmax}}$	Fisher et al. 2008
	f_{SM}	Soil moisture constraint	$f_{SM-ATI} = \frac{ATI - ATI_{min}}{ATI_{max} - ATI_{min}}$	García et al. 2013
Plant variables	f_{APAR}	PAR fraction absorbed by green vegetation	$f_{APAR-MODIS}$	García et al. 2013
	f_{IPAR}	PAR fraction intercepted by total vegetation	$f_{IPAR} = m_2 \cdot NDVI + b_2$	Fisher et al. 2008
	f_c	Fractional vegetation cover	$f_c = f_{IPAR}$	Campbell & Norman 1998
	LAI	Leaf Area Index	LAI_{MODIS}	García et al. 2013
Energy variables	Rn_s	Net radiation to the soil	$Rn_s = Rn \cdot e^{(-k_{Rn}LAI)}$	Norman et al. 1995
	λEp_c	Priestley-Taylor potential evapotranspiration for canopy	$\lambda Ep_c = \alpha_{PT} \frac{\Delta}{\Delta + \gamma} (Rn - Rn_s)$	Norman et al. 1995
	λEp_s	Priestley-Taylor potential evapotranspiration for flooded soil	$\lambda Ep_s = \alpha_{PT} \frac{\Delta}{\Delta + \gamma} (Rn_s - Sw - G)$	Soucha et al. 1996; this study
	λEp_s	Priestley-Taylor potential evapotranspiration for dry soil	$\lambda Ep_s = \alpha_{PT} \frac{\Delta}{\Delta + \gamma} (Rn_s - G)$	Norman et al. 1995

Table 4.1. Equations and variables used in the PT-JPL-daily model, plant variables and energy variables f_{APAR} is the fraction of Absorbed Photosynthetically Active Radiation; f_{IPAR} is the fraction of intercepted photosynthetically active radiation; T_{opt} is optimum temperature for plant growth (25 °C); T_{am} is the daily mean air temperature (°C); $f_{APARMAX}$ is maximum f_{APAR} ; ATI is the observed apparent thermal inertia index (°C–1); ATI_{min} is the seasonal minimum ATI ; ATI_{max} is the seasonal maximum ATI . Rn is daily net radiation (Wm⁻²). Values for parameters: k_{Rn} =0.6 (Impens & Lemeur, 1969); m_2 =1.0, b_2 =–0.05 (Fisher et al., 2008); γ (psychrometric constant)= 0.066 kPa C⁻¹; α_{PT} =1.26 Priestley–Taylor coefficient; Δ is the slope of the saturation-to-vapor pressure curve (Pa K⁻¹).

The formulation of soil evaporation required two different approaches due to the existence of flooded and not-flooded conditions during the year. The estimation of λE_s for the flooding season, with or without vegetation, is based on the Priestley-Taylor potential evapotranspiration for soil adjusted to flooded conditions (Eq. 4.3) as described in Soucha et al. 1996 (Table 4.1). The water storage term (Sw) (Eq. 4.4) in the Albufera was based on water level and temperature hourly measurements taken in the field. Additionally, this term was also estimated based on the average

water level in combination with flooding detection techniques (Tornos et al., 2015) and water temperature measurements in the Ebro Delta and the Albufera.

$$\lambda E_s = \lambda E_{ps} \quad (4.3)$$

$$S_w = C_p \cdot m_w \cdot \left(\frac{dT}{dt} \right) \quad (W \cdot m^{-2}) \quad (4.4)$$

Where:

m_w (mass of water per m²) $(g \cdot m^{-2})$

h (height of superficial water layer) (m)

C_p (specific heat of water) $(J \cdot g^{-1} \cdot K^{-1})$

dT/dt = (variation of temperature in an hour) $(K \cdot s^{-1})$

Out of the flooding season the potential evaporation in the rice fields for dry conditions (Table 1) was reduced by a soil moisture constraint (Eq. 4.5), f_{SM} , based on thermal inertia (Table 1).

$$\lambda E_s = f_{SM} \lambda E_{ps} \quad (4.5)$$

The apparent thermal inertia (ATI) index was developed by Price in 1977, linking theoretically diurnal surface temperature (T_s) to thermal inertia. According to Verstraeten et al., (2006), increasing soil water content alters soil thermal conductivity and decreases diurnal surface temperature variation. In this study we have used ATI as described in Garcia et al (2013), following the equations described in Verstraeten et al (2006) and Mitra and Majumbar (2004) (Eq. 4.6). It combines surface temperature (T_s) and albedo (α) to measure thermal response in soil material due to changes in its temperature (Nearing et al., 2012).

$$ATI = C \frac{1-\alpha}{T_{SdMax} - T_{SdMin}} \quad (4.6)$$

The albedo parameter (α) is the result of the combination of white and black broadband albedo of MCD43B3 product from MODIS, as described in Rasmussen et al. (2014). Maximum surface (T_{SdMax}) and minimum surface (T_{SdMin}) temperature have been modelled based on MOD11A1 and MYD11A1 products from MODIS. The correction factor C (Eq. 4.7) normalizes the changes in solar irradiation with the latitude, ϑ and the solar declination angle, φ .

$$C = \sin\vartheta \sin\varphi (1 - \tan^2\vartheta \cdot \tan^2\varphi) + \cos\vartheta \cdot \cos\varphi \cdot \arccos(-\tan\vartheta \cdot \tan\varphi) \quad (4.7)$$

Three model cases were validated with Eddy Covariance λE measured in the FLUXNET site pixel (Table 4.2): (1) λE model relying on R_n and water level measured; (2) λE model based on R_n modeled; (3) λE model counting on R_n modeled and S_w based on water level information from agricultural data. In this last version, flooding dates were estimated based on the detection of phenometrics in a combination of spectral indices annual time series, as described in Tornos et al. (2015).

The first version would be useful for locations counting on a more complete dataset of meteorological variables and field data, while version 2 and 3 are potentially useful for locations counting only on more basic datasets, and particularly for developing countries.

Version	Rn	Sw	Data source
1	Measured	Calculated with measured data	Fluxnet tower (Saler) Field Measurements
2	Estimated	Calculated with measured data	MODIS dataset Field Measurements
3	Estimated	Calculated with water level estimates and remote sensing techniques (Tornos et al. 2015)	MODIS dataset Agricultural data

Table 4.2. Versions of the PT-JPL-daily model studied.

4.3.2 Model setting for flooded ecosystems

The annual dynamics of soil heat flux (G) and Sw data measured in the flux tower in 2010 were studied in order to consider the inclusion of G and Sw in the model adjustment for flooded soils in rice fields. Additionally, the relations among G, Sw and λE were analyzed to fully understand the annual variations in the energy balance in coincidence with flooding and phenological changes in rice fields. Finally, the time series of G and Sw were analyzed for the period 2010-12 on a daily basis, in order to study the long-term behaviour of these variables in relation with rice field phenology and flooding conditions.

The closure errors of the energy balance for the field data taken in 2010 were calculated to study their reliability and the differences in the error depending on the formulation considered during the flooding season. The equation was tested including only G, only Sw and both. The relative errors (e) were also calculated, following eq. 4.8, 4.9 and 4.10, where H is the sensible heat flux.

$$e = (\lambda E + H) / (R_n - G) \quad (4.8)$$

$$e = (\lambda E + H) / (R_n - Sw) \quad (4.9)$$

$$e = (\lambda E + H) / (R_n - G - Sw) \quad (4.10)$$

4.3.3 Rn estimation.

Net radiation (Rn) values were modelled and afterwards validated with Rn measurements from the flux tower. The estimates of Rn were calculated based on the balance between incoming and outgoing, shortwave and longwave, radiation fluxes (4.11), as described in Garcia et al. (2007), relying mostly on remote sensing data.

$$R_n = R_{n_s} + R_{n_l} = (R_{SI} \downarrow + R_{SO} \uparrow) + (R_{LI} \downarrow + R_{LO} \uparrow) \quad (Wm^{-2}) \quad (4.11)$$

The rest of the variables needed, incoming shortwave radiation (R_{SI}) and maximum temperature, were obtained from a weather station situated in the flux tower. Rn shortwave daily (R_{ns}) was estimated as described in (Eq. 4.12), being α the albedo, and transformed into instantaneous values following Jacksons et al. 1987.

$$Rn_s = R_{SI} \downarrow \cdot (1 - \alpha) \quad (Wm^{-2}) \quad (4.12)$$

Rn longwave (R_{nL}) was calculated in an instantaneous basis as the balance between outgoing longwave radiation (R_{LO}) and the incoming longwave radiation (R_{LI}). R_{LO} was calculated as described in (Eq. 4.13), where σ is the Stefan–Boltzmann constant ($5.67 \times 10^{-8} Wm^{-2}$), T_{SI} is the surface temperature (K) at the time of satellite overpass, and ϵ_s is the broadband emissivity for the surface. R_{LI} was computed following Idso & Jackson, (1969) (Eq. 4.14), where T_{AIR} is air temperature and c and d are constant described in the original model.

$$R_{LO} \uparrow = -\epsilon_s \sigma T_{SI}^4 \quad (Wm^{-2}) \quad (4.13)$$

$$R_{LI} \downarrow = \sigma \cdot T_{AIR}^4 \cdot \left(1 - \left(c \cdot e^{(-d \cdot (T_{AIR} - 273.15)^2)}\right)\right) \quad (Wm^{-2}) \quad (4.14)$$

Finally, Rn was computed as a balance of fluxes in an instantaneous basis and transformed to daily values following Jacksons et al (1987). This method was originally intended for estimating R_{SI} . According to Bisht et al (2005), the diurnal cycle of Rn can be formulated, similarly to R_{SI} in Jacksons et al. (1987), as a sinusoidal model from a single Rn instantaneous estimate for clear sky-days. These circumstances are present in both locations, and accordingly, this assumption has been considered suitable. However, there is a source of error derived from the estimation of the local times in which Rn becomes positive and negative, that coincides with sunrise and sunset in R_{SI} (Jackson et al., 1987) but is displaced from these points in Rn (Batra et al., 2006). This is due to the effect of Rn during nighttime, negative in value, that is not accounted in the model and decreases the real value of Rn daily, displacing the point where it becomes positive and negative (Fig 4.3).

Fig. 4.3. Rn daily behaviour in the flux tower in El Saler (the Albufera).

This displacement was estimated by Batra et al., (2006), in 45 minutes in their study site. However, this bias between the estimated and the real Rn values is variable through the year in temperate zones, as nighttime duration changes. This consistent overestimation of Rn is similar among the years, month to month, if they are observed in time series. In this study, this difference was corrected by the use of a monthly coefficient derived from the study of the relation between daily modelled and measured Rn. The main hypothesis is that this difference of values between modelled and measured Rn is variable through the year and mostly similar among years for the same month. The coefficient was calculated with daily measured and modelled Rn for a two-year time series (2011-12), and was validated for a year (2010).

4.3.4 Model validation in the Albufera.

The three λE model versions were validated at Saler FLUXNET site for the year 2010. This specific year was selected based on data quality and the availability of a complete dataset for each variable needed. Measurements of λE from Eddy Covariance fluxes were obtained in a rice field location at 30 minutes time step. Then, the daily average values of the measured data were calculated to be used in the assessment of the accuracy in value and dynamics of the model results.

4.3.5 Assessment of the λE time series (2010-12)

The time series of the model results in the first and second model cases were analyzed for the period 2010-12 on a daily basis. Based on that, the long-term dynamics of λE in the Albufera were studied in relation with rice field phenology and flooding conditions.

4.3.6 Evaluation and comparison between the Albufera λE and the Ebro Delta λE .

The daily values of λE for the year 2012 were calculated in the Ebro Delta and compared with the results of the third version of the model in the Albufera. These two location have the particularity of being ecosystems with almost identical ecological and hydrological features, presenting differences in data availability. Net radiation values were estimated based on Garcia et al. (2007), as explained in section 4.3.3, and water level values were estimated based on agricultural data. Flooding dates were obtained with an approach based on the detection of phenometrics in a combination of spectral indices, as described in Tornos et al. (2015). Water temperature measurements were acquired from a water quality station placed in the rice fields.

4.4. Results

4.4.1 Model setting for flooded ecosystems

Analysis of the field variables: Soil Heat Flux (G) the Water Storage Term (Sw), and λE

From March to middle-May, with dry bare soil G showed an increasing trend (Fig. 4.4) until the flooding of the fields (beginning in middle-May). At this moment G started to decrease gradually, taking relatively low values during the flooding periods: (1) the growing season, (May-September) and (2) the winter flooding (October-February)). Sw showed (1) highly constant values during the growing period and (2) highly dispersed values during the winter flooding, characterized by the existence of a high water layer free of any vegetation.

Fig. 4.4. G and Sw evolution for 2010 in flooding conditions and non-flooding conditions (NF) in El Saler (the Albufera).

λE presented also three distinct patterns. During the non-flooded period, from March to middle May (Fig. 4.5) λE values were highly dispersed. In the rice growing season (middle-May until

middle-September) λE increased as rice grows reaching maximum values in July and decreasing afterwards. During the winter flooding (October to March) λE showed a decreasing trend and high dispersion. λE increased again in February, presenting highly dispersed values.

Fig. 4.5. λE , G and Sw variations for 2010 in El Saler (the Albufera).

The dynamics of G and Sw were analysed to study the relationship between the two parameters for the time series 2010-12 and the consistence of the seasonal tendencies detected for 2010. The Sw term showed stronger variations than G, and no trend in the values was detected for the three-year period studied (Fig. 4.6). However, the seasonal dynamics and relations between G and Sw described in the Fig. 4.4 appeared consistently in all the years studied. In general, the absolute values taken by Sw were much greater than those taken by G when the soil was flooded. However, it was noticed that G took higher values during the non-flooding period in all the years studied, being accounted between 10-30 w/m².

Fig. 4.6. G and Sw variations time series for 2010-12 in flooding conditions and non-flooding conditions (NF) in El Saler (the Albufera).

The existence of dynamic relationships between G, Sw and water level in the fields (Wl) was also explored by means of the Granger Causality Test (1969), modified by Geweke, for the time series 2010-12 (Table 4.3). These test results for $Sw \rightarrow G$ causal relationship were significant for 1-40 lags, while its value was not significant for the inverse relationship, $G \rightarrow Sw$ in the same horizon. The test results were also significant for $Wl \rightarrow G$ ratio on the horizon from 1 to 7 lags being, however, not significant beyond 8 lags.

Dynamic relationship	Number of lags included in test regressions (k)													
	1	2	3	4	5	6	7	8	9	10	21	25	30	40
$Sw \rightarrow G$	48.22	33.45	26.14	20.77	16.43	14.33	12.88	11.15	9.29	8.14	3.23	2.68	2.37	2.46
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$G \rightarrow Sw$	1.39	3.78	0.88	0.69	0.78	0.84	0.69	0.59	0.88	0.83	0.67	0.61	0.71	0.83
	0.24	0.02	0.45	0.60	0.56	0.54	0.68	0.78	0.54	0.60	0.87	0.93	0.87	0.76
$Wl \rightarrow G$	33.66	15.01	8.61	5.81	4.07	2.94	2.37	1.78	1.42	1.31	0.53	0.57	0.63	0.65
	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.08	0.18	0.21	0.96	0.96	0.94	0.95
$Wl \rightarrow Sw$	1.66	2.00	2.46	1.95	1.59	2.18	2.03	2.19	1.83	2.02	3.68	5.44	4.10	2.86
	0.20	0.14	0.06	0.10	0.16	0.04	0.05	0.03	0.06	0.03	0.00	0.00	0.00	0.00

Table 4.3: Granger Causality tests for variables G, Sw and Wl with the null hypothesis: variable in the left side does not cause variable in the right side. Significant causal relationships are highlighted in bold.

Energy balance closure error

Table 4.4 shows the number of observations with closure error smaller than a specific threshold for the different formulation of the energy balance in El Saler during the flooding stages (rice growing season and winter flooding).

	$R_n = \lambda E + H + G$	$R_n = \lambda E + H + S_w$	$R_n = \lambda E + H + G + S_w$
N° values $e < 25\%$	121/365	188/365	195/365

Table 4.4. Number of observations in which the relative error is smaller than 25% for three formulations of the energy balance.

Including S_w and G (Table 4.4) in the model resulted in the highest number of observations with $e < 25\%$, although the formulation based only in S_w achieved almost the same results. They also presented similar average error values. These closure errors were higher in February, March and April, in coincidence with the non-flooded season (Fig. 4.7).

Fig. 4.7. Energy balance closure error (E) for 2010 including S_w during the flooding season in El Saler (the Albufera).

The energy balance closure of the formulation based on S_w and G (Fig. 4.8.a) and the formulation based only in S_w (Fig. 4.8.b) were evaluated deriving linear regression coefficients from the daily average values of the dependent flux variables ($\lambda E + H$) against the independently derived available energy ($R_n - S_w - G$) or ($R_n - S_w$), in each case. The first formulation achieved slightly better results than the formulation based only in S_w (Fig. 4.8.a and b), although both were within the range of closure errors in FLUXNET sites, below 20% (Wilson et al., 2002).

Fig. 4.8. Regression of the energy balance closure error in $Rn = \lambda E + H + Sw + G$ (a) and in $Rn = \lambda E + H + Sw$ (b) for 2010.

4.4.2 Rn estimation

Rn time series (2010-12)

The time series of modelled Rn was calculated and compared with the field values for the period 2010-12 to identify inter-annual dynamics (Fig. 4.9.a). The modelled Rn values presented a similar annual dynamic than measured Rn values. However, the modelled dataset presented a bias in comparison with field data from the flux tower. This bias produced a consistent overestimation of the net radiation, with higher differences in winter and lower ones in summer. The occurrence and relative value of these errors were similar each year, and the general dynamics and tendencies in

both variables were analogous for this period. In order to correct this bias, Rn values were improved based on a time series-based correction (Fig. 4.9.b), as explained in section 4.3.3.

Fig. 4.9. Rn measured and Rn modelled time series for 2010-12 in El Saler (the Albufera) before correcting the bias (a) and after correcting the bias (b).

Validation of modelled Rn 2010

The adjusted modelled values of Rn for 2010 were afterwards validated with Rn field data (Fig. 4.10), achieving $R^2=0.95$. This dataset was used as a parameter in one of the cases studies of the model in section 4.4.3.

w/m2

Fig. 4.10. Rn measured data compared with Rn predicted and adjusted values in El Saler (the Albufera).

4.4.3 Validation of λE for 2010

The PT-JPL-daily model, adjusted for flooded ecosystems, was used to estimate λE and was validated for 2010 in El Saler in three cases: (1) measured Rn and water level values; (2) modelled Rn and measured water level and (3) modelled Rn and water level based on agriculture data from the farmers. Out of the 365 observations 195 values were selected based on the closure error with most of the gaps occurring during the winter flooding (65% gaps) and the non-flooded period (64% gaps).

Table 4.5 shows the assessment of the three versions of the model.

	r^2	MAE ^a	RMSE ^b
(1) PT-JPL-daily (<i>Rn measured</i>)	0.75	26.41	20.44
(2) PT-JPL-daily (<i>Rn modelled</i>)	0.68	40.13	31.06
(3) PT-JPL-daily (<i>Rn modelled/Water level estimated</i>)	0.70	40.49	31.33

^a Mean absolute difference MAE= $(\sum_{i=1}^n |O_i - P_i|/n)$.

^b Root Mean Square Error RMSE= $[(\sum_{i=1}^n (O_i - P_i)^2/n)]^{1/2}$.

Table 4.5. Errors in the estimation of λE with PT-JPL daily in the three cases studied in El Saler (the Albufera).

The best correlation values were showed when both Rn and water level were measured ($r^2=0.75$), while the second case presented lower r^2 values.

Fig. 4.11 shows λE predicted in the first case studied and λE measured in El Saler Flux Tower for 2010. Both the measured and the modelled λE values showed an increase as the rice grows, reaching the maximum in July and decreasing as rice plants wilt.

λE p w/m2

(a)

w/m2

(b)

Fig. 4.11. Model version 1. Regression of λE predicted values and λE measured values (a) and data distribution (b) in El Saler (the Albufera) in 2010.

The model underestimated slightly the values of λE in the rice heading date while values were similar for most of the rice growing season. During the winter flooding, both the modelled λE and the measured λE kept a decreasing tendency as the radiation and temperature drops, from October to January. Stronger differences were found out of the flooding season, from February to the end of April. In this period, measured values showed higher dispersion than the modelled λE , which followed a sustained increasing tendency, as temperature and radiation grows.

In case (2) (Fig. 4.12) the number of R_n data gaps was higher due to cloudy remote sensing data and weather data gaps. The results reproduced correctly the annual λE dynamics although R^2 values were slightly lower than (1), underestimating λE values.

Fig. 4.12. Model version 2. Regression of λE predicted (R_n modelled) and λE measured values (a) and data distribution (b) in El Saler (the Albufera) in 2010.

The third case of the model relied on R_n modelled data and agricultural data for the water level in the rice fields. In general, estimated values were lower than field data (Fig.4.13).

Fig. 4.13. Model version 3. Regression of λE predicted (R_n modelled and water level estimated) and λE measured values (a) and data distribution (b) in El Saler (the Albufera) in 2010.

4.4.4 Assessment of the λE time series (2010-12) in the Albufera. Case 1 and 2.

λE was studied for the period 2010-2012 in the first and second cases of the model, as explained in section 4.4.3. The number of results in both versions of the model was affected principally by the lack of measurements of water temperature and water level in the fields. The dynamics of both

series were similar, and the use of Rn measured or modelled did not affect the results significantly (Fig. 4.14).

Fig. 4.14. λE Time series with R_n field data and with R_n modelled for 2010-12 in El Saler (the Albufera).

4.4.5 Estimation of λE in the Ebro Delta and comparison with the results in the Albufera

The PT-JPL-daily model with modelled R_n , previously validated in El Saler, was applied for the year 2012 in the Ebro Delta and compared with the values obtained in El Saler (Fig. 4.15). A lower number of results were produced in this zone due to a greater number of cloudy images in comparison with El Saler, especially in spring. Additionally, the lack of water temperature data in January conditioned the information obtained about the winter flooding period. The general annual dynamics of λE followed the phenology of rice in the Ebro Delta, with the peak close to the maximum vegetative development and a decreasing tendency until the harvest, in September. During the winter flooding, from October to December, the λE showed a mild decreasing tendency until last month of the year. A group of values took abnormally high values in the second half of May.

Fig. 4.15. λE predicted in the Ebro Delta and λE measured values in El Saler (the Albufera) for 2012.

In comparison with El Saler, the general patterns of the λE during the rice season and the winter flooding in the Ebro Delta were similar. The values for the rice growing season in the Delta were slightly higher than those of El Saler, especially near to the heading date, at the end of July, while those in the non-flooded season (February to April) took lower values.

4.5. Discussion

In this work, we studied an adaptation of the PT-JPL model to rice ecosystems and we assessed the dynamics of the model and their main variables by means of time series in two different scenarios: (1) locations with field data for all the variables (El Saler with measured R_n) and (2) locations counting only on basic data (El Saler with R_n estimated, and El Saler and the Ebro Delta with R_n and water level estimates).

The main variables of the energy balance were analysed in order to select the most appropriate formulation of the model in rice ecosystems. The inclusion of both S_w and G resulted in the lowest closure error with an R^2 of 0.85 (Fig.4.8), proving the importance of considering both variables in rice ecosystems. The R^2 values were in line with the closure error in other FLUXNET sites (Wilson et al., 2002). It should be noted that the underestimation of the heat storage terms in FLUXNET towers has been found to have an important effect in the energy balance closure error (Wilson et al., 2002). Furthermore, the closure error in eddy covariance stations is worse over wetlands and crops than over drier surfaces (Stoy et al. 2013). This is also supported by Souch et al. (1995), as they highlighted the importance of water and soil heat storage in energy balance in wetlands, finding that it may constitute 35% of the daytime balance. The R^2 values relative errors (Table 4.4)

suggest that the formulation including S_w and G during the flooding season and G for the non-flooding season would be the most appropriate for estimating rice ecosystem energy balance. The study of the time series 2010-12 (Fig. 4.6) showed the inter-annual consistence in the seasonal behaviour of S_w and G , suggesting a strong link with temperature and phenological cycles.

The Granger Causality Test (Table 4.3) showed the existence of a causal relationship of S_w over G highly significant for the following 5 days. The same pattern does not exist at all in the opposite direction. Thus G time series prediction could be improved by using the available S_w values. As the flooding stage begins, a large amount of energy is stored in the water layer which controls the heat conduction to the soil.

The soil heat flux (G) (Fig. 4.4) ranged between 0 and 30 Wm^{-2} , with a strong increasing trend through the non-flooded period due to the absence of the water storage effect and the increasing temperatures in spring, taking highest values just before the flooding. This highlighted the important contribution of G also in bare soils. In this period, characterized by partially wet bare soil due to occasional spring precipitation, λE values were very dispersed (Fig 4.5) while G values were more stable.

During the rice growing season both S_w and G decreased as the rice season progressed, probably due to the canopy shading together with the increasing importance of λE as rice increases its leaf area index (Fig. 4.5). This behaviour is in line with previous findings of Yan et al., (2012), detecting a decreasing tendency beneath the rice canopy in λE , H and water temperature as the rice season advances. The stability of G and S_w values may be due to the effect of rice canopy protecting the water table from radiation and winds. This may make it possible to estimate the effect of S_w and G in the energy balance equation during the growing season when no data is available.

In the winter flooding period, G took lower and more stable values than the other fluxes (Fig. 4.5), suggesting an important effect of the wind in the water layer that may produce evaporation without significant effects in soil temperature. Souch et al. (1996) highlighted the effect of wind in increasing the sensible heat values with respect to water and soil storage in wetlands, due to the effect of turbulent heat transfer. On the other hand, the highly variable S_w values may be a consequence of the increased exposure of the water table to the effect of wind variability and changes in temperature. Drexler et al. (2004) noted the rapid variations in water and soil storage in wetlands in spring and autumn, due to atmospheric instability, resulting in sudden changes in water storage values.

Net Radiation was modelled and compared with R_n measurements for the period 2010-12. R_n predicted values presented similar dynamics than R_n measured, but all the values showed a bias, with stronger differences in winter (Fig. 4.9.a). This bias was surely due to the limitations of the model (section 4.3.3) to reproduce the emission of radiation during night time, as it was originally proposed to simulate the behaviour of radiation during day time. Bisht et al. (2005) detected this source of error, being daily R_n estimates 15% higher than measured ones. Accordingly, shorter daylight in winter would produce higher errors when nighttime loss is not considered in comparison with summer. It should be noted that the correct estimation of this parameter in λE modelling is

greatly important, even in flooded ecosystems, as it is the main factor controlling ET (Sun & Song, 2008). The bias was corrected based on the assumption that this deviation was similar for the same period of different years, and accordingly a time-series based correction was applied as described in Methods 4.3.3. The adjusted values of Rn (Fig. 4.9.b) were very similar in value and behaviour than those measured for the time series 2010-12, and thus they were considered appropriate to be used in the λE model. Since it is not always possible to count on reliable Rn data in many zones, the adjustment of this bias would be useful to improve the results of the Rn model and thus obtaining better λE estimates.

The three versions of modelled λE were validated with field data from the Flux Tower of El Saler for 2010. The model with Rn measured (Table 4.5) presented a correlation with field data of 0.75. The R^2 , MAE and RMSE values were similar to those obtained in the Mediterranean Region by Garcia et al. 2013 with this model, even though the ecological conditions were completely different. It should be taken into account that the closure in eddy flux measurements has been reported to be about 80% (Wilson et al., 2002), so the results obtained cannot be considered out of range. The λE obtained with the PT-JPL-daily model in the first case showed the same annual dynamics than the field values (Fig. 4.11), especially during the growing cycle of rice (May-September). Deviation was more important out of the flooding season (February-April) and in the winter flooding (October-February), which additionally counted on fewer data to validate (about 35% of the total dates). Since the model doesn't take into account wind dynamics, it is possible that the effect of the maritime winds in this period without vegetation was the main cause of this phenomena. This statement is supported by the findings of Sun & Song (2008), which stated the importance of advective energy out of the growing season in wetlands. This effect was, however, lower in importance during the growing season in comparison with Rn.

The second version of the model (Fig. 4.12), based on Rn modelled values presented similar dynamics than the first version, although errors were slightly higher. The study of λE time series (2010-12) for both versions of the model (Fig. 4.14) showed the consistency of this pattern in different years. Therefore, these results demonstrated the feasibility of applying the second version of the model in locations lacking Rn datasets.

A third version of the model, based on Rn modelled and Sw estimated from agricultural information was validated in El Saler (Fig. 4.13) and afterwards applied in the Ebro Delta, a zone lacking reliable Rn and water level measurements (Fig. 4.15). As these zones presents similar ecological conditions the results of the model can be considered comparable. This version in El Saler achieved similar results than the second one (Table 4.5). The results in the Delta showed an annual pattern similar to that in the Saler (Fig. 4.15). The λE general dynamics in the Delta were consistent with the phenological stages and flooding periods in this location for this year. However, it should be noted that the estimates in the Saler took lower values than the measured data (Fig.4.13), and thus the values in the Delta may be underestimated. This kind of approach, based only on basic meteorological data could be useful to estimate water needs in rice_ecosystem in zones with low availability of field data, and especially in developing countries.

The results of this work remarks the feasibility of using the PT-JPL-daily model, adapted for rice ecosystems in areas presenting similar ecological conditions than El Saler. It should be noted that the access to reliable information about flooding dates and water level is crucial for a correct estimation of water storage term and, therefore, a correct estimation of energy balance in flooded ecosystems (Souch et al. 1995). In this regard, the lack of field measurements could require the use of R_n modelled, as described in this work, and the application of remote sensing methodologies to detect the flooding of the fields. However, it should be explored an improvement of the results and an alternative methodology to estimate water level in rice fields to avoid the use of agricultural data or field measurements.

4.6. Conclusions.

This study has explored the adaptation of the PT-JPL-daily model to rice ecosystem in coastal locations of the Mediterranean Region. Three different versions were studied to find suitable adjustments for locations with or without field data. A correction of the modelled R_n based on time series dynamics was performed to improve the results.

The principal findings of this study were:

- The PT-JPL-daily model reproduced adequately the main dynamics of λE in rice ecosystems during the rice growing season, but it was less reliable in reproducing the variability present out of this period.
- Sw was a key variable in the energy balance of rice fields during the flooding season, and accordingly it has to be accounted in λE models.
- The addition of G in the model also improved results, especially out of the flooding season, when it took higher values.
- R_n was modelled adequately adding a correction of the bias based on a time-series approach.

The generalization of these results may be possible in similar ecosystems in other regions, especially rice paddies in coastal locations, although its potential use in other flooded ecosystems such as wetlands should be studied. The best results were obtained when R_n and Wl data are available, although other approaches based on modelled R_n data and remote sensing flooding detection techniques are possible for regions lacking reliable field data. As the determination of Sw is crucial, further studies are needed to improve the determination of this component of the model based on remote sensing techniques.

This approach may be useful to improve large-scale estimation of water necessities and water balances for rice paddies in countries and regions lacking reliable λE measurements. Particularly, the results obtained may be helpful to establish water policies and to study water necessities for specific locations. Additionally, this approach based on remote sensing may allow the study of long-term λE dynamics, providing insights of the effects of Climate Change in water need trends.

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CHAPTER 5

Conclusions

Chapter 5. Conclusions.

5.1 General conclusions

This work proposed a combination of methodologies to assess water dynamics in rice ecosystems, based on remote sensing, meteorological and agricultural data. The combined estimation on rice area (chapter 2), duration of the flooding period (chapter 3) and evapotranspiration (chapter 4) makes it possible the monitoring of water use in rice ecosystems at different spatial and temporal scale in an integrated manner. This kind of information is crucial for water resource planning, food security and climate change monitoring at global level, and would be particularly useful to provide reliable data in the context of the Sustainable Development Goals from the Agenda 2030 and the Paris Agreement.

NDVI and SASI indices, applied in a simple methodology based on time series profile comparison methods (SAM), proved their potential to provide accurate rice maps in zones with different flooding and phenological dynamics. The levels of accuracy were especially relevant in SASI, with similar or better results than those showed in other studies with higher spatial resolution.

An approach based on the integration of four spectral indices (NDVI, NDWI(1), NDWI(2), SASI) to detect specific phenometric in rice was developed, taking advantage of the information content in different spectral regions summarized in each index. The results obtained highlighted the added value of this kind of approaches.

The SASI index demonstrated an outstanding capability to identify transitions in land cover, differentiating dry soil, flooded soil and vegetation dynamics. This feature was key to: (1) discriminate effectively rice dynamics from those of other similar land covers, such as wetlands or other irrigated crops, and (2) identify phenological transitions in the rice paddy dynamics. It was particularly interesting the determination of the flooding date for its potential use in other studies. This result highlights the applicability of the Spectral Shape Indexes to monitoring natural resources.

The PT-JPL-daily model adjusted to flooded conditions in rice ecosystems provided adequate estimates on water consumption through evapotranspiration for the year 2010 in the Saler. These results prove the applicability of a physically sound model with low data requirement to estimate evapotranspiration on wetlands. In addition, the model provided evapotranspiration time series estimates for the same site since 2010 to 2012 at a daily frequency.

The main novelty in the implementation of the PT-JPL-daily model has been the adjustment for intermittent flooded conditions, a feature that make difficult the estimation of evapotranspiration. In order to adjust the model to wetland conditions the water heat storage and soil heat flux dynamics were assessed and integrated in the model.

In a global context of water scarcity, the approach proposed would make it possible to provide reliable temporal and spatial information on water use dynamics in rice ecosystems, appropriate under different water management practices and with low data requirements. This would especially interesting to be applied in regions were field and statistical information is scarce, particularly in developing countries.

5.2 Specific highlights

The main highlights of this thesis are:

- SASI provides useful information on transitions between bare soil, vegetation, and water in rice fields being able also to discriminate rice field from other similar land uses.
- NDWI(1), NDWI(2) and SASI presented much better capability to assess variability out of the growing season than NDVI showing the importance of the SWIR spectral to detect flooded soils.
- A considerable consistency between the time series statistical analysis (i.e. ACF) and the phenometric approaches was showed.
- The ACF provided useful information for assessing spectral indices dynamics and patterns related to vegetation and flooding dynamics in rice.
- The water heat storage (Sw) was a key variable in the energy balance of rice fields during the flooding season, and accordingly it has to be accounted in λE models.
- Net radiation (Rn) was modeled adequately adding a correction of the bias based on a time-series approach.

5.3 Future work

Although the main potential of this method based on MODIS images is specially indicated for rice mapping in medium-size rice areas or regional studies, the use of higher spatial resolution sensors should be explored for studies in small-size rice areas. In this regard, the increasing availability of data and resolutions from new sensors, such as the new ESA Sentinel-2 sensors (Druch et al., 2012) may provide the opportunity to improve the results obtained.

The methodology to assess phenological and flooding dynamics could be implemented to be applied in specific years. In such cases, smoothing and validation procedures would be necessary.

As the determination of water storage heat (Sw) is essential, further studies are needed to improve the determination of this component of the PT-JPL-daily model based on remote sensing techniques. An alternative methodology to estimate water level in rice fields to avoid the use of agricultural data or field measurements could be also explored in order to increase the applicability of the model.

CHAPTER 6

References

Chapter 6. References

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