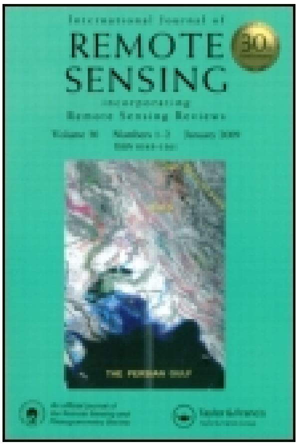

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REVIEW ARTICLE

Remote sensing of rice crop areas

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Rice means life for millions of people and it is planted in many regions of the world. It primarily grows in the major river deltas of Asia and Southeast Asia, such as the Mekong Delta, known as the Rice Bowl of Vietnam, the second-largest rice-producing nation on Earth. However, Latin America, the USA, and Australia have extensive rice-growing regions. In addition, rice is the most rapidly growing source of food in Africa. Rice is therefore of significant importance to food security in an increasing number of low-income food-deficit countries. This review article gives a complementary overview of how remote sensing can support the assessment of paddy rice cultivation worldwide. This article presents and discusses methods for rice mapping and monitoring, differentiating between the results achievable using different sensors of various spectral characteristics and spatial resolution. The remote sensing of rice–growing areas can not only contribute to the precise mapping of rice areas and the assessment of the dynamics in rice-growing regions, but can also contribute to harvest prediction modelling, the analyses of plant diseases, the assessment of rice-based greenhouse gas (methane) emission due to vegetation submersion, the investigation of erosion-control-adapted agricultural systems, and the assessment of ecosystem services in rice-growing areas.

1. Introduction to the benefits of remote sensing of rice-based agricultural systems

Remote sensing provides the essential technology and methodology to monitor, map, and observe rice-growing ecosystems over large areas, at repeated time intervals, to interpret rice-growing areas under a variety of aspects. Rice is the staple food for more than half of the world's population, mostly in developing countries in Asia, Africa, and Latin America (Fairhurst and Dobermann 2002; FAO 2004c), and is thus of significant importance to food security (FAO 2004b). On a global scale, in the year 2011, 720 million tonnes of paddy rice were produced, of which more than 90% was produced in Asia. For 2012, a slight increase in global production is forecasted (Table 1).

However, food security is uncertain, as the growth rate of the world's rice production has slowed down during recent years (FAO 2004c; IRRI 2006) and current annual rice consumption has exceeded annual rice production. With a growing global population, with an expectation of ∼9 billion people for the year 2050 (UN 2011), the world food demand is expected to increase as well (FAO 2004c; Sakamoto et al. 2009b; Shen et al. 2009).

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Table 1. Global paddy rice production in million tonnes.

	World	Asia	Africa	South America	North and Central America	Europe	Oceania
2011	720	651.9	25.3	26.5	11.1	4.5	0.7
	100%	90.54%	3.51%	3.68%	1.54%	0.63%	0.1%
2012	732.2	665.6	26.1	24.5	10.9	4.4	0.9
	100%	90.89%	3.56%	3.35%	1.48%	0.6%	0.12%

Source: FAO Rice Market Monitor (2012).

To face this challenge, new planting methods and an increase in the rice-growing area to ensure sustainable and/or higher agricultural productivity with higher yields are needed (Sakamoto et al. 2009b). But, the decreasing availability of arable land, the decreasing availability of water for irrigation (Thiruvengadachari and Sakthivadivel 1997), and the effects of global climate change could hamper the accomplishment of an increasing food security based on rice cultivation (Thiruvengadachari and Sakthivadivel 1997; Gregory, Ingram, and Brklacich 2005).

There is a strong need for an effective means to monitor rice cultivation and the related socio-economic and global environmental aspects to provide and improve information on rice-growing ecosystems and rice growth conditions (Le Toan et al. 1997), as well as to assess the balance between rice production and demand (Kim, Hong, and Lee 2008; Shen et al. 2009). Reliable, quantitative, non-destructive information on current crop status and various variables related to crop physiology and biochemistry can be obtained in an instantaneous and cost-effective manner by means of remote sensing (Bouman 1995; Thiruvengadachari and Sakthivadivel 1997; Casanova, Epema, and Goudriaan 1998; Dawson et al. 1999; Chang, Shen, and Lo 2005; Nguyen and Lee 2006; Hatfield et al. 2008; Shen et al. 2009). Remote-sensing-derived information delivers important support for decision processes for multi-annual agricultural development (cropping system and technological improvements), as well as for seasonal reactions directly linked to the rice growth status (McVicar 2005; Panigrahy et al. 2005). Instead of time- and cost-consuming conventional field investigations, standardized methods can be used to assess the spatial and temporal environmental variations that influence crop growth and health (Fang et al. 1998; Moulin, Bondeau, and Delecolle 1998; Shen et al. 2009).

Remote sensing is capable of providing timely and reliable information for various purposes related to rice agricultural systems such the following (Shibayama and Akiyama 1991; Le Toan et al. 1997; Thiruvengadachari and Sakthivadivel 1997; Casanova, Epema, and Goudriaan 1998; Moulin, Bondeau, and Delecolle 1998; Kobayashi et al. 2001; Zhang, Wang, and Wang 2002; Bastiaansen and Ali 2003; Chang, Shen, and Lo 2005; Panigrahy et al. 2005; Nguyen and Lee 2006; Diuk-Wasser et al. 2007; Salas et al. 2007; Yang, Cheng, and Chen 2007; Hatfield et al. 2008; Lee et al. 2008; Shen et al. 2009):

- mapping and monitoring the extent of rice-growing ecosystems;
- monitoring and assessment of rice growth and health status;
- assessment of cropping pattern and cropping system efficiency;
- estimation of crop-growth-related parameters (leaf area index (LAI), biomass, fraction of absorbed photosynthetically active radiation (fAPAR), and evapotranspiration);
- precision agriculture (yield prediction, application of fertilizer and pesticides for sustainable agriculture, and discrimination between crops and weeds);

- input and improvement and extension of crop growth and yield models;
- agricultural ecosystem evaluation and assessment of negative environmental impacts, such as land degradation and soil salinity;
- better understanding of the relationship between rice plants and their environment;
- hydrologic assessment and modelling (soil moisture, monitoring of water use and productivity in fields, and relationship between crop yield and hydrological processes);
- measurements of disease incidence (drought and pests); and
- estimation of climate-change relevant emissions of methane fluxes.

The results of the above activities/approaches, combined with geographical information system (GIS) and other ancillary data, have built a valuable basis for spatial decision support in farm management, sustainable irrigation management, irrigation method adjustments, cropping optimization, farming system intensification, and policy definition in food provision management (Thiruvengadachari and Sakthivadivel 1997; Bastiaansen and Ali 2003; Chang, Shen, and Lo 2005; McVicar 2005; Sakamoto et al. 2009b).

1.1. Spatial distribution of rice-growing areas

Rice grows over the large spatial domain between 60° latitude and 80° longitude, covering a wide range of landscape types (Xiao et al. 2006). It can be found in the tropical and subtropical regions in Asia, contributing to 24% of the overall cropland (Leff, Ramankutty, and Foley 2004) in temperate regions in Europe (Italy and Spain), Africa (Nile Delta and Valley in Egypt, Sudan, and Madagascar), the USA (Mississippi, Missouri, and Louisiana), the Middle East (Iran and Iraq), and Central Asia (Portmann et al. 2008) (Figure 1).

Even though growing areas are so widely distributed, specific ecological conditions are needed for growing rice, and critical influences on rice distribution and yield are determined by various factors (Shao et al. 2001). Temperature is the most critical factor for growing rice (De Datta 1981). Temperature, measured as the annual accumulated temperature in degree days, has to be 2000–4500°C for ≥10°C in a region to produce one rice crop per year, 4500–7000°C for ≥10°C for two rice crops a year, and 7000°C for ≥10°C for the production of a maximum of three rice crops a year (Shao et al. 2001). The distribution

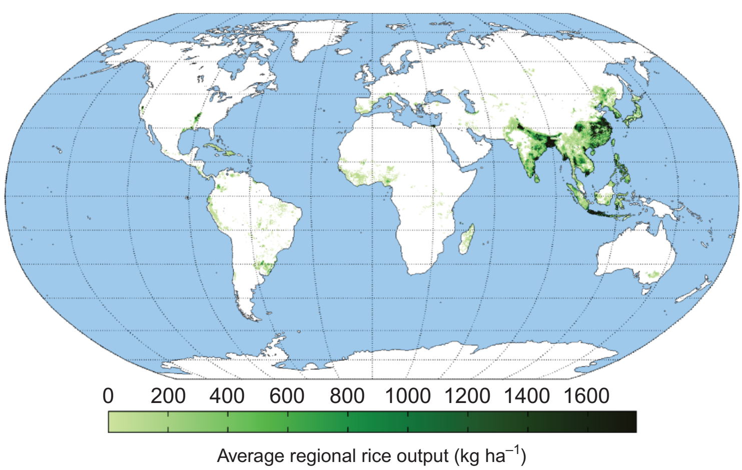


Figure 1. Rice-growing areas around the world (modified after Monfreda, Ramankutty, and Foley 2008).

and yield of specific rice varieties is determined by different amounts of solar illumination durations (De Datta 1981; Shao et al. 2001), day lengths, relative humidity, and wind speeds during the growing period (De Datta 1981). Rice plants prefer sandy or clayey soils with good water-holding capacity, fertility, permeability, and a near-neutral pH value (Shao et al. 2001). Rainfall, irrigation, evaporation, and soil permeability are the factors that determine water supply and availability (Shao et al. 2001). Rice-growing areas are mostly wetland ecosystems (LaCapra et al. 1996); therefore, they need a high amount of precipitation (or irrigation). The important water supplies delivered by seasonal precipitation over the tropics and sub-tropics of the Indian subcontinent and Southeast Asia are driven by the dominating monsoon climate system (Xiao et al. 2006). Even in irrigated areas, the individual monsoon system alternations of wet and dry seasons and the amount of water brought determine the beginning of a cropping season (Barker, Herdt, and Rose 1985).

1.2. Characteristics of rice plants, the growing cycle, and the farming system

Knowledge of rice plant physiology and growth stages is indispensable to the success of applications and the planning stages of remote-sensing projects (Van Niel and McVicar 2004a, 2004b). Thus, we briefly address the characteristics of rice plants, their growing cycles, and the possible farming systems.

Annual rice belongs to the genus *Oryza*, tribe *Oryzeae*, and family Gramineae (De Datta 1981). The most important cultivated species are *Oryza sativa* L., with its origin in Asia, and *Oryza glaberrima*, the common species originating in West Africa (De Datta 1981; Barker, Herdt, and Rose 1985). The simple morphology consists of roots, culms, and leaves, which form tillers. Later on, when the rice seeds mature, an inflorescence is produced as a panicle. The International Rice Research Institute classifies three growth phases: (1) the vegetative phase from germination to panicle initiation, (2) the reproductive phase from panicle initiation to flowering, and (3) the ripening phase from flowering to mature grain (De Datta 1981; IRRI 2009b). The growing cycle encompasses the three growth phases, which include 10 growth stages: 0, germination; 1, seedling; 2, tillering; 3, stem elongation; 4, panicle initiation/booting; 5, heading; 6, flowering; 7, milk stage; 8, dough stage; and 9, mature grain. Stages 0–3 constitute the vegetative phase, stages 4–6 correspond to the reproductive phase, and stages 7–9 describe the ripening phase (IRRI 2009a) (Figure 2).

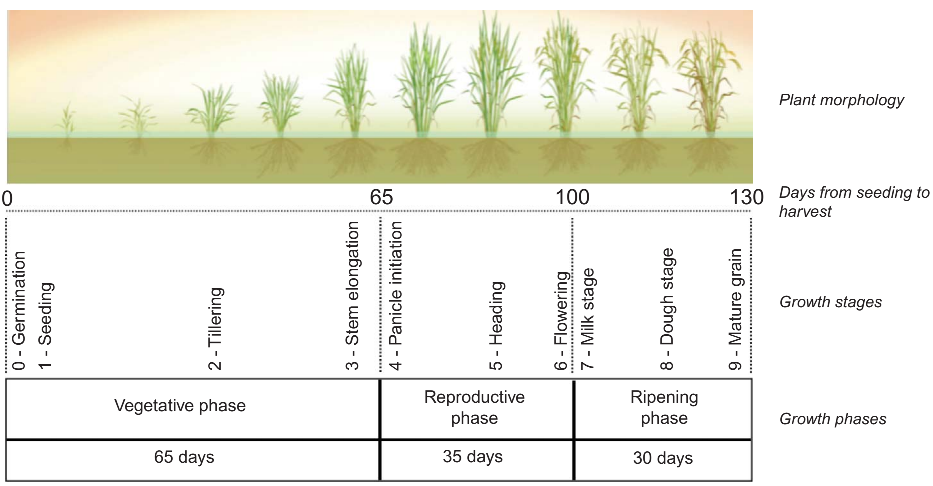


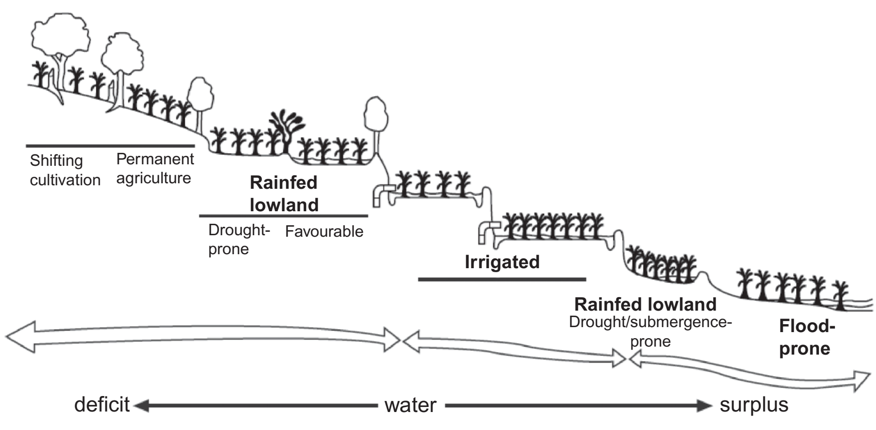
Figure 2. Rice plant morphology with growth phases and stages (modified after IRRI 2009a, 2009b).

The duration of the growing cycle depends on the variety of rice species and the climate conditions and is defined by the length of the vegetative phase. The reproductive phase is about 35 days and the ripening phase is about 30 days in tropical regions (IRRI 2009b). Tropical rice varieties have an average life cycle of 110–120 days, and the duration of the life cycle in temperate regions is about 140–150 days (Le Toan et al. 1997). Finally, the life cycle takes 3–6 months from germination to maturity, depending on the cultivar and the environment in which it is grown (Yoshida 1981; Casanova, Epema, and Goudriaan 1998).

In temperate and colder tropical climates, only one crop is cultivated per year and the cropping duration is longer. However, yields are often higher (De Datta 1981). Under tropical conditions with optimal irrigation, rice can be harvested two or three times a year. Depending on variety, growing seasons and crop calendars are different. The determinant factor for the beginning of a crop cycle is scheduled by the water distribution scheme (Le Toan et al. 1997). According to this circumstance, the crop calendar can differ in neighbouring groups of fields. Le Toan et al. (1997), for example, observed a shift of up to 6–8 weeks between fields within a given region in Indonesia.

Rice is the only crop that grows under wetland conditions (Bouman, Lampayan, and Tuong 2007). Therefore, rice-growing ecosystems can be classified into four major farming systems based on water regime, drainage, temperature, soil type, and topography (Bambaradeniya and Amarasinghe 2003) (Figure 3).

First, upland or dryland rice is found in rainfed mountains or plateaus. The rice is dry-seeded, due to the lack of humidity, mostly poor soils, and the absence of surface or rhizosphere water accumulation (Bambaradeniya and Amarasinghe 2003). Yields are often very low (around 1 t ha^{-1}). Upland rice farming can be found in Brazil, Madagascar, India, and Southeast Asia. The amount of produced upland rice represents approximately 13% of the rice-planted area in the world and 4% of the global rice production.



Upland	Rainfed lowland	Irrigated	Flood-prone
Level to steeply sloping fields; rarely flooded, aerobic soil; rice direct seeded on plowed dry soil or dibbled in wet, non-puddled soil	Level to slightly sloping, bunded fields; non-continuous flooding of variable depth and duration; submergence not exceeding 50 cm for more than 10 consecutive days; rice transplanted in puddle soil or direct seeded on puddle or plowed dry soil; alternating aerobic to anaerobic soil of variable frequency and duration	Leveled, bunded fields with water control; rice transplanted or direct seeded in puddle soil; shallow flooded with anaerobic soil during crop growth	Level to slightly sloping or depressed fields; more than 10 consecutive days of medium to very deep flooding (50 to more than 300 cm) during crop growth; rice transplanted in Puddle soil or direct seeded on plowed dry soil; aerobic or anaerobic soil; soil salinity or toxicity in tidal areas

Figure 3. Rice land ecosystems (Pingali, Hossain, and Gerpacio 1997).

Second, rainfed lowland rice ecosystems have a non-continuous flooding of variable depth (1–50 cm) and duration. The water availability for the bounded fields depends on the duration of rainfall (Bambaradeniya and Amarasinghe 2003). Lowland rice fields have anaerobic soil conditions with stagnant water for at least 20% of the cropping duration (Bouman, Lampayan, and Tuong 2007). Only 25% of the total rice area and 17% of the world production grow in this important farming system, which is often found in Africa and Madagascar. The yield per hectare is around 2.5 tonnes.

The third farming system is irrigated lowland rice, growing in bounded flooded fields mostly in Asia, and the seeds are pre-germinated and grown in wet seedbeds. The availability of pond irrigation is maintained for at least 80% of the crop's duration (Bouman, Lampayan, and Tuong 2007). Rice productivity is very high due to the permanent availability of water during the growing season. The controlled water depth lies from 5–10 cm. The yield is approximately 5 t ha^{-1} during the rainy season. In the case of irrigated rice, one to three harvests per year are possible. Therefore, this is the most important farming system globally. Irrigated rice accounts for 55% of the world rice areas and about 75% of the world production (Fairhurst and Dobermann 2002).

Fourth, deepwater and tidal wetland farming systems (flood prone), with water depths of 0.5–3 m, are supplied by rivers, lakes, or tides in river mouth deltas. This system can be found in Southeast Asia, West Africa, and South America. Due to the climate risks of droughts and floods, productivity is often low. The system is important for small farms in flood-prone areas with a yield of 1t ha^{-1} (UNCTAD 2011).

On an annual basis, irrigated rice is five times more productive than rainfed rice, 12 times more productive than deep-water rice, and reaches 100 times the productivity of upland rice (Fairhurst and Dobermann 2002). Wetland rice is thus the most important farming system, and therefore the basis for most studies and research work. In these studies, the often-used synonym for rice fields is *paddy fields* or *paddies*. The word originates from the Malayan word *padi*, which means rice (De Datta 1981). Figure 4 shows the distribution of rice-cropping ecosystems in Southeast Asia.

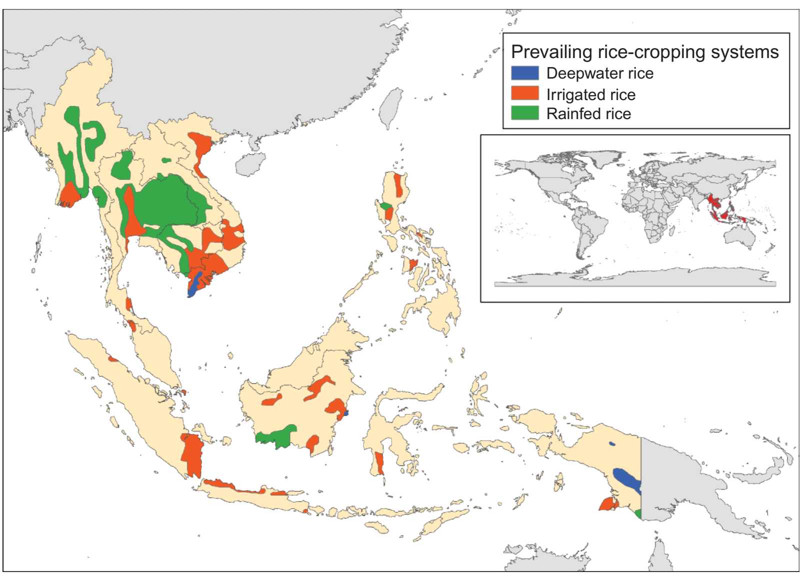


Figure 4. Distribution of rice-cropping systems in Southeast Asia (modified after Bridhkitti and Overcamp 2012).

1.3. Environmental impacts of rice-growing ecosystems

Rice-growing areas are among the world's most enduring, environmentally sound, and productive agro-ecosystems (IRRI 2006). The temporary aquatic agro-ecosystem of paddy rice fields is characterized by a coherent environment, with biotic and non-biotic components involved (Halwart and Gupta 2004). A major component of a well-performing agro-ecosystem is its biodiversity, which contributes to the services of the ecosystem. The losses or changes in species richness or composition implicate a reduction or a loss in other directly related functions or species, which in turn hampers or destroys the balance of the agro-ecosystem (Tilman et al. 2002; Heong 2008). Tropical rice-growing wetland ecosystems deliver important services that directly affect people (IRRI 2006). However, at the same time, rice-based ecosystems are vulnerable to human-induced impacts. The ability to provide goods and services can be reduced through the excessive application of fertilizers and pesticides. As an example, one of the most important services in tropical rice-growing ecosystems is pest suppression (e.g. planthopper). The indication of insecticides in tropical rice is virtually unnecessary and counterproductive because they disrupt the normally high levels of pest suppression inherent in the plant. However, nowadays, the use of broad-spectrum, long-residual insecticides has disrupted the natural pest control mechanisms of rice. Rice insecticides are among the most toxic agrochemicals and accounted for nearly 15% of the global crop insecticide market in 1988 (Rola and Pingali 1993).

Fertilizers and pesticides are often applied prophylactically and lead to an increase of toxins in ground and surface waters (Tilman et al. 2002). The impact and damage of the over-application of fertilizers and the improper application of pesticides in rice-growing ecosystems are severe and long lasting. Groundwater pollution, eutrophication, soil degradation, and nitrogen contamination result in direct impacts on human health via the food chain and water usage (Rola and Pingali 1993; Pingali, Hossain, and Gerpacio 1997; Li et al. 2004; IRRI 2006). Furthermore, the continuous presence of water encourages the occurrence of diseases (e.g. it acts as breeding places for the main vector mosquitoes causing malaria, dengue, and schistosomiasis), which may affect rice farmers (IRRI 2006; Diuk-Wasser et al. 2007).

The excessive use of fertilizers refers to the fact that nitrogen affects crop productivity and is important to enhance and stabilize crop growth and yield production (Lee et al. 2008). Rice yield is closely related to the N-status before the heading stage. N-topdressing at the panicle initiation stage is crucial for rice yield and quality. Therefore, the assessment of the canopy nitrogen status by remote-sensing techniques at these growth stages can provide important information for nitrogen fertilization applications (Lee et al. 2008).

Rice growth and yield are also very vulnerable to climate impacts and climate changes, such as global warming with shifts in temperature (e.g. rising night-time temperatures), shifts in rainfall patterns, extreme weather events (storms, cyclones, and typhoons), lengthening of the growing season, droughts (especially in rainfed systems), and flooding (Shibayama et al. 1993; Pingali, Hossain, and Gerpacio 1997; Gregory, Ingram, and Brklacich 2005; IRRI 2006; Sakamoto et al. 2009b).

1.4. The role of water in rice-growing ecosystems

Wetland rice is the most important farming practice of rice globally; therefore, a large amount of water is consumed. About 2500 l of water needs to be supplied by rainfall and/or irrigation to a rice field to produce 1 kg of rough rice (Bouman 2009). The estimated water use by evapotranspiration of all rice fields in the world is estimated to be

859 cubic kilometres per year (Bouman 2009). Around one-fourth to one-third of the world's developed freshwater resources are used for rice irrigation. Due to population growth, increasing urban and industrial demand, pollution, and resource depletion, freshwater is becoming a scarce and more valuable natural resource. Thus, there is a high need to improve water resource management and water-saving technologies, such as the introduction of aerobic rice varieties and new irrigation regimes and techniques (Bouman and Tuong 2001; Xiao et al. 2005, 2006; Bouman 2009). In particular, multi-cropping paddy rice farming prevents an adequate drying period in the ecosystem, due to the fast and continuous flooding of rice fields. Several negative effects on the chemical and biological processes within the soil (retarded rate of humus decomposition, decreased rate of soil nitrogen mineralization, ammonia volatilization, soluble iron and manganese accumulation, salinity build up, and water logging) are the consequence (Greenland 1997; FAO 2004a; Bouman, Lampayan, and Tuong 2007). The resulting anaerobic wetland soils contribute to greenhouse gases through methane emissions to the atmosphere (Cao et al. 1996; Pingali, Hossain, and Gerpacio 1997; Dobermann and Fairhurst 2000; Hengsdijk and Bindraban 2008). After CO_2, methane (CH_4) is the second important greenhouse gas, with an estimated 5–10% of the total global emissions (Bouman, Lampayan, and Tuong 2007). It is the final product of the anaerobic fermentation processes of soil organic matter. As methane has a 28-fold greenhouse gas potential compared to CO_2, methane emission induced by flooded rice fields cannot be neglected when budgeting the global carbon balance (Le Toan et al. 1997; Xiao et al. 2005, 2006; Salas et al. 2007).

2. Reflectance characteristics of rice in remote-sensing data

Monitoring and mapping paddy rice in a timely and efficient manner is very important for the assessment of agricultural and environmental productivity, analyses of food and water security, and studies related to greenhouse gas emissions, among many others (Xiao et al. 2006). As ecological and agronomic variables are related to the spectral or backscatter characteristics of Earth's observation data, the latter can provide indirect information about plant growth and development, and can thus support this endeavour (Patel et al. 1985; Inoue et al. 2008). Particularly, information on phenological development is a fundamental key to crop monitoring because it describes the actual state of cultivated species and varieties and their relationship with pedoclimatic conditions (Boschetti et al. 2009).

The reflectance spectrum of a rice crop canopy is the result of a complex relationship between its biophysical and biochemical attributes (Yang and Cheng 2001; Yang, Cheng, and Chen 2007). Changes in one or more conditions of growth such as climate, water supply, and nutrition may strongly affect the reflection characteristics and the reflection pattern. However, if these circumstances are similar, different varieties show similar temporal spectral responses (optical data) (Patel et al. 1985).

2.1. Reflectance characteristics of rice in optical remote sensing data

During the first weeks after transplanting, while rice seedlings are recovering from the damage caused by transplantation, the percentage of ground cover is $<15\%$ (Chang, Shen, and Lo 2005). Underlying water and the soil surface dominate the reflectance characteristics. At the active tillering stage (stage 6, 9 weeks after the transplanting), the tiller number and leaf area will have increased rapidly. Twelve weeks after transplanting, the reflectance in the near-infrared (NIR) region reaches the highest value of the season, while reflectance

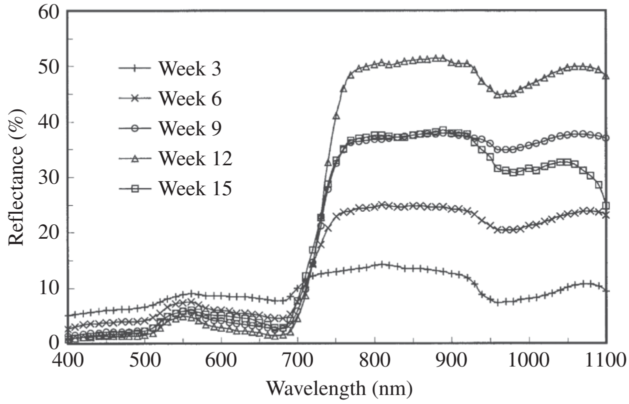


Figure 5. Reflectance spectra of rice plants during different growth stages showing temporal variability (Chang, Shen, and Lo 2005).

in the visible portion reaches the lowest value (Chang, Shen, and Lo 2005). The inflection point of the red edge correlates well with the chlorophyll content of the leaf.

The visible part of the incoming radiation is strongly influenced by the absorption processes of leaf pigments (Figure 5), such as chlorophyll *a* and *b* and carotenoids (Blackburn 1998). The concentration of these compounds is strongly related to the physiological status, which finally affects the productivity of a plant (Blackburn 1998). Assessment of photosynthetic functioning is one of the most important bases for the diagnosis and prediction of plant growth, as well as for the estimation of carbon exchange between ecosystems and the atmosphere (Inoue et al. 2008). Variations of the foliar chemical content are very distinct during the ripening and senescence stages as well as indicative of physiological stress (Shibayama and Akiyama 1991; Blackburn 1998; Hatfield et al. 2008). Red reflectance can be considered to be inversely proportional to the greenness of the rice crop (Casanova, Epema, and Goudriaan 1998). 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, Epema, and Goudriaan 1998). NIR reflectance viewed over time varies according to biomass, increasing from a minimum of 15% at early tillering to a maximum of 50% at heading (Casanova, Epema, and Goudriaan 1998). Then it diminishes, corresponding to the decrease in biomass due to the decay and loss of leaves, to a final value of approximately 33% (Casanova, Epema, and Goudriaan 1998). Figure 6 depicts this progression in multispectral data.

In most cases, under real-world conditions, the spectra of rice are influenced by the water surrounding the plant. The water regime system thus has an important impact on the canopy reflectance spectra (Xue et al. 2005). The reflectance in the visible range (460–710 nm) within an intermittent irrigation system is obviously higher than that of the shallow water system in the mid-infrared region (1480–1650 nm), while it is significantly lower than that of the shallow water system in the NIR region (760–1220 nm) (Xue et al. 2005). The LAI, shoot numbers, and biomass in an intermittent irrigation system are lower than in a shallow water system, which results in higher reflectance in between the leaf layers and therefore relatively low reflectance in the NIR. The leaf structure within an intermittent irrigation system is usually compact and the leaf chlorophyll content is lower, which results in relatively lower absorption and higher reflectance in the visible bands (Xue et al. 2005).

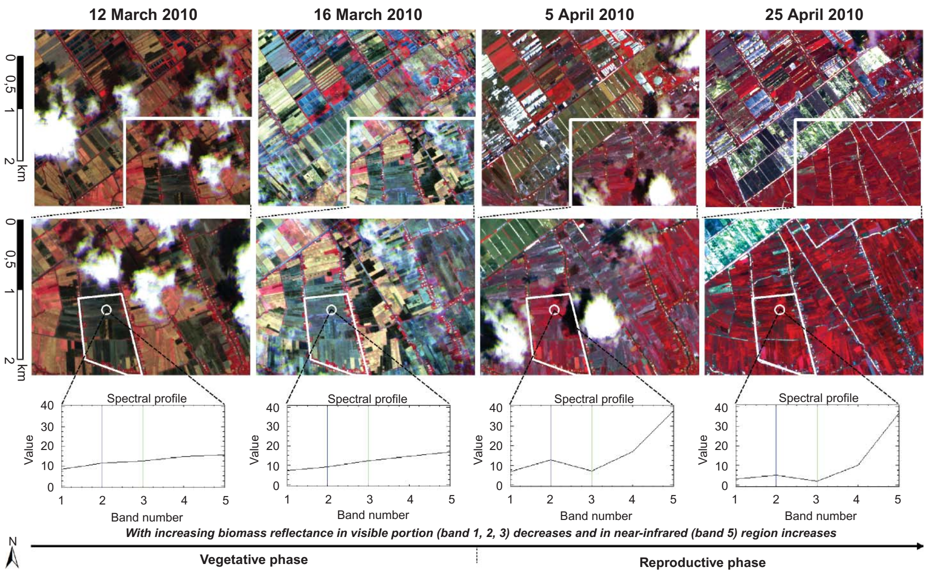


Figure 6. Reflectance characteristics of rice in optical remote-sensing data (rapid eye) obtained from Rice Research Farm, Can Tho, Vietnam (Mekong Delta).

2.2. Backscatter characteristics of rice in radar data

Understanding the synthetic aperture radar (SAR) backscatter of rice fields as a function of crop growth is essential for the development of reliable and robust methods to retrieve crop growth parameters and crop phenology information (Choudhury, Chakraborty, and Parihar 2007). The following section describes the general backscatter mechanism of rice and the temporal dynamic of backscatter during the growing period for different frequencies, polarizations, and incident angles. The relationship between the frequency, polarization, and growth parameters is also depicted.

The radar backscatter of agricultural crops is extremely sensitive to the structure of the canopy and that of the underlying soil surface (Bouman 1995). This sensitivity is especially strong for crops with distinct, vertical, elongated canopy elements, such as those found in cereals: stems, leaves, and ears (Bouman 1995). The underlying surface is characterized by a changing amount of vegetation-covered area and the presence of water. Consequently, the main scattering mechanism results from the radar wave–vegetation–soil–water interaction. The most important parameters accountable for backscatter are usually plant height, plant biomass per unit volume, gravimetric water content, and plant structure (Ribbes and Le Toan 1999; Dong, Sun, and Pang 2006). Figure 7 shows the main scattering mechanisms with direct scattering.

The backscatter signatures of each frequency band usually have unique patterns that depend on the growth of the rice canopy (Inoue et al. 2002). In general, a large dynamic range of backscatter, which varies from the pre-transplanting to the pre-harvesting stage, can be observed in the case of rice crops. Prior to transplanting, the recorded radar signal is very low due to specular reflection from the flooded fields (Kurosu, Fujita, and Chiba 1997; Le Toan et al. 1997; Panigrahy et al. 1999; Chen and McNairn 2006). At this stage, rice fields can be easily detected and separated from other non-rice areas in the radar images because of the significant backscatter difference between flooded areas and non-flooded areas (Chen and McNairn 2006). Flooded field data are thus essential for identifying

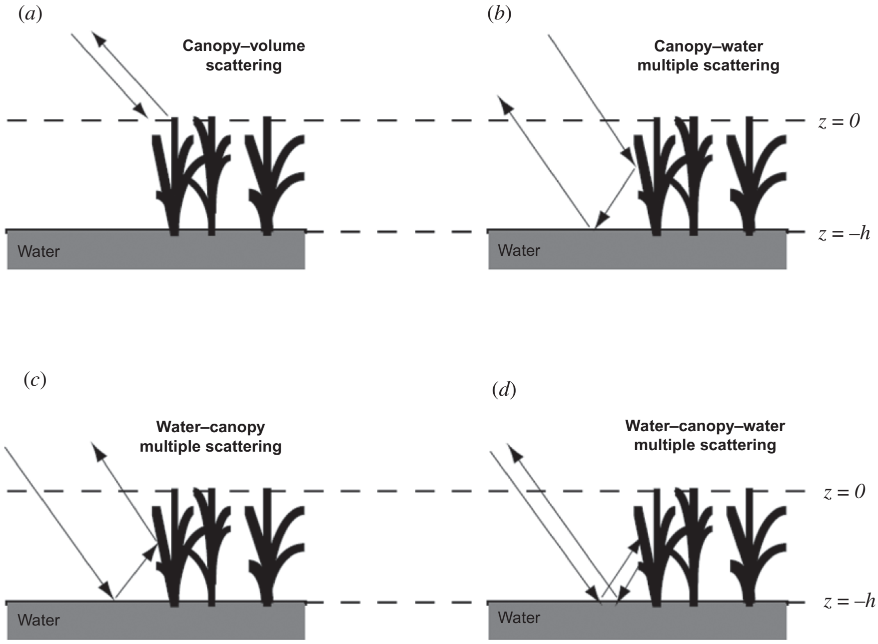


Figure 7. Major scattering mechanisms in the rice canopy (modified after Le Toan et al. 1997). (*a*) Direct scattering from the scatterer (canopy–volume scattering); (*b*) reflection of the boundary followed by a single scattering from the scatterer (canopy–water multiple scattering); (*c*): opposite to (b) (water–canopy multiple scattering); and (*d*): a reflection by the boundary followed by a single scattering from the scatterer and further followed by a reflection of the boundary (water–canopy–water multiple scattering.

rice fields from multi-temporal radar data (Kurosu, Fujita, and Chiba 1997; Choudhury, Chakraborty, and Parihar 2007). Volume scattering from within the rice canopy, and multiple reflections between the plants and water surface, result in an increase in backscatter during the vegetation phase, reaching a maximum at the heading stage (Chen and McNairn 2006). As the crop ripens, the plant water content decreases (Chen and McNairn 2006), and so do stem and leaf densities (Lim, Koo, and Ewe 2008). This results in a reduction in the backscatter coefficient during the ripening stage until harvest (Chen and McNairn 2006). Although the densities of the grains increase at this stage of the rice growth, the stems remain the dominant contributor to the total backscattering coefficient for all polarizations (Lim, Koo, and Ewe 2008). This temporal backscatter pattern is unique to rice crops. Variations in backscatter over the growing season for rice are much larger than in any other agricultural crop (Chen and McNairn 2006; Choudhury, Chakraborty, and Parihar 2007). This is visualized in Figure 8.

Despite the growth stage of the rice crop, the chosen wavelength as well as the polarization and incidence angles also influence the backscattered signal. Dependant variations have been discussed in many articles, and it would be out of the context of this article to elaborate on all these. Very detailed measurements and analyses based on scatterometer and other radar data over the course of the growing season can be found in Lim et al. (2007), Lim, Koo, and Ewe (2008), (2009), Kim, Hong, and Lee (2008), Lam-Dao et al. (2007), and especially in Inoue et al. (2002), Le Toan et al. (1997), among others.

Related to polarization, it can be mentioned that there seem to be the following broadly applicable interrelations: VV-polarized backscattering coefficients are higher than

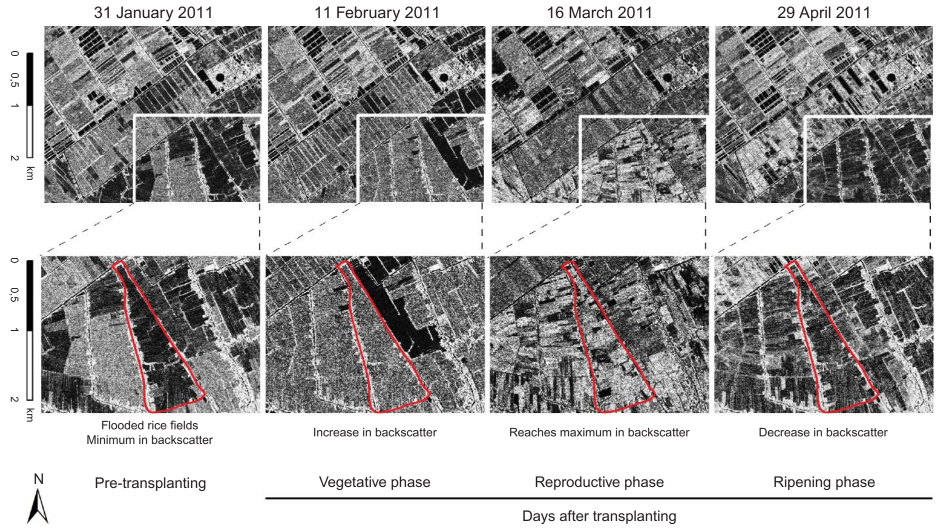


Figure 8. Backscatter characteristics of rice in Terra SAR-X radar data according to growth phases obtained from Rice Research Farm, Can Tho, Vietnam (Mekong Delta).

HH-polarized backscattering coefficients in the early rice growth stages (Kim, Hong, and Lee 2008). This is due to the physical structure of the rice plant, which consists of mainly short vertical leaves and stems during the early rice growth stages (Lim, Koo, and Ewe 2008). Conversely, HH-polarized backscattering coefficients are higher than VV during a large part of the rice-growing season, due to the attenuation of the wave by the vertical structure of rice plants (Lam-Dao et al. 2007; Kim, Hong, and Lee 2008; Bouvet et al. 2009). Thus, multi-polarization and multi-angular data will definitely bring additional information for rice growth monitoring throughout the season (Lim et al. 2007). However, apart from polarization, incidence angles and the radar frequency utilized play a large role. Inoue et al. (2002), for example, found that the temporal change in the backscattering coefficients is more dynamic at smaller incident angles for the Ka and Ku bands, while it is more dynamic at larger incident angles for the C and L bands. In the C-band, where the dominant scattering mechanism of HH and VV is the double-bounce vegetation–water mechanism (Lam-Dao et al. 2007), HH-polarized signals reach saturation at the heading point. The reason may be the decrease in water and the change of physical size of the rice in the harvest period (Chen et al. 2007). In the L-band domain, HH-polarized data yield a very low backscatter during the initial flooding period, followed by increasing backscatter during the vegetative growth period, and a levelling off of backscatter during the heading/ripening stage (Inoue et al. 2002 in Salas et al. 2007). This increase during the growth period coincides with the increase in biomass and has been explained by the dominant vegetation–water interaction scattering mechanism (Le Toan et al. 1997). Le Toan et al. (1997) also investigated backscatter coefficient ($\sigma°$) as a function of rice parameters based on European Remote Sensing 1 (ERS-1) SAR C-band VV polarized data, noting that at the end of the productive phase $\sigma°$ values reach from –8 to –6 dB and remain stable until the end of the cycle. Generally speaking, they underlined that the strong temporal variation of the radar backscatter is the most striking characteristic of rice fields, compared to that of other cover types.

Figure 9 presents the temporal variations of backscattering coefficients at different incidence angles and polarizations for different bands, as observed by Kim, Hong, and Lee

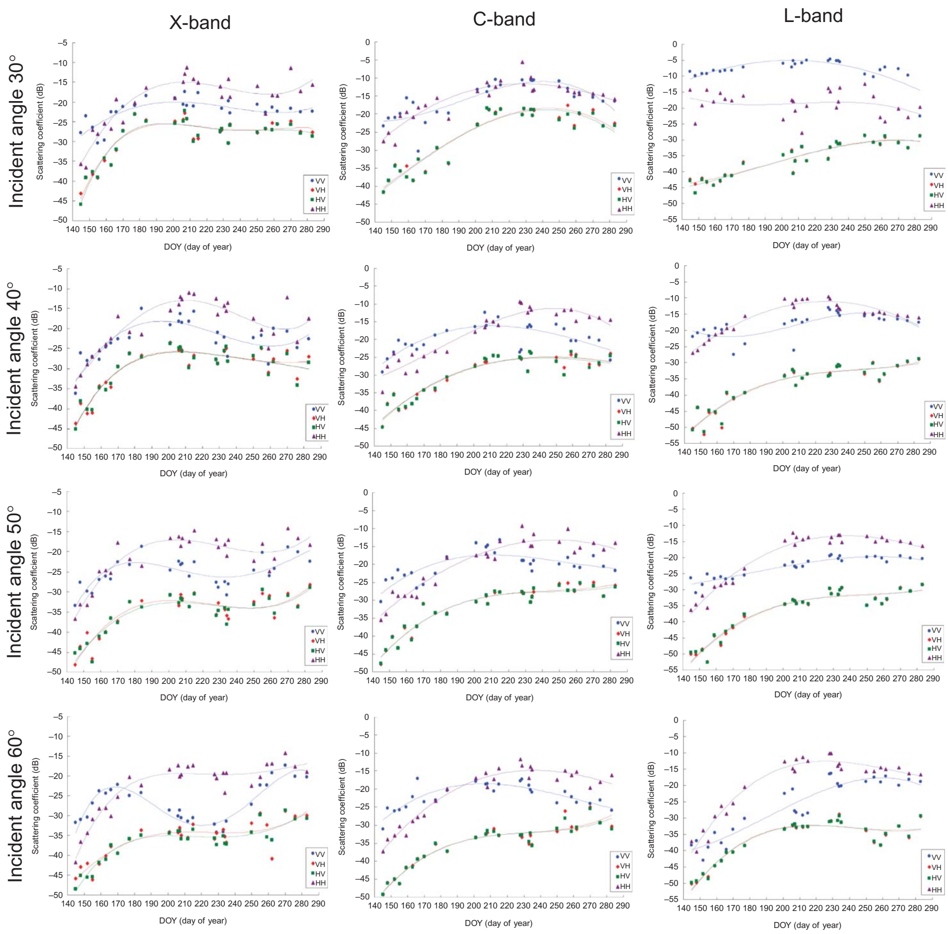


Figure 9. Temporal variations of backscattering coefficients at different polarization and incident angles 30°, 40°, 50°, and 60° for the X, C, and L bands (modified after Kim, Hong, and Lee 2008).

(2008). Similarly to the conclusions from this figure, Inoue et al. (2002) also found that the VV polarization in the L-band has little sensitivity at steeper incident angles (25° and 35°), but showed more dynamic seasonal change at larger angles (45° and 55°). In their studies, the backscattering coefficient in the X-band during the ripening period reversed with the incident angle, from decreasing (at 25°) to increasing (at 55°), while no similar phenomenon was found in the Ka and Ku bands (Inoue et al. 2002). The observed X-band response may be attributed to the penetration depth and canopy structure (Inoue et al. 2002). In their studies, the seasonal trends at higher frequencies (the Ka, Ku, and X bands) clearly showed that microwave backscatter is highly sensitive to the size of dominant elements. Higher frequencies are dominated by canopy scattering (and are thus also sensitive to early growth changes, in the month after transplanting when LAI < 1.5), while lower frequencies, like the L and P bands, have dominant canopy or significant soil backscatter contributions to the total backscatter (Inoue et al. 2002). Based on these complex but unique signatures, SAR backscatter can be related to rice crop biomass and can be used to map parameters relevant for rice production and finally yield estimation (Chen and McNairn 2006).

However, next to the characteristics of the radar radiation, the structure of the rice field (planting density, etc.) also plays an important role. For example, at the L-band, the variation in the scattered return signals from rice fields with different structures can be large because of constructive and destructive interferences between rice plants as a result of different plant spacing (Wang et al. 2005). Without knowing the plant spacing, the inversion of the rice biomass from the scattering results will be difficult at the L-band (Wang et al. 2005). They also found that for the C-band, the rice field structure has less effect on the returns (about 6 cm compared to 24 cm for the L-band) (Wang et al. 2005). On the contrary, Bouman (1995) came to the conclusion that row spacing had a pronounced effect on the radar backscatter. Generally, the particular parameters identified by various researchers, as well as the level of significance and the strength of the correlations, are inconsistent (Inoue et al. 2002). Backscatter signals from vegetated surfaces are affected by so many factors, including plant biomass, stand structure, soil moisture, and roughness, as well as their interactions with sensor configurations, such as frequency, polarization, and incident angle, that in some cases, statements valid in 100% of the cases cannot be derived (Inoue et al. 2002).

3. Remote sensing of rice-growing areas

A lot of research effort has been directed towards the assessment of crop yield and eco-physiological variables using remote sensing in the optical, thermal, and microwave wavelength domains, in combination with modelling approaches (Bastiaansen and Ali 2003; Doraiswamy et al. 2004; Inoue et al. 2008 etc.). Typical crop characteristics and biophysical variables, which are derived from remote-sensing data in rice-growing areas, include the assessment of the following.

- *Wet biomass* (WBM) (Patel et al. 1985; Xue et al. 2004).
- *Above-ground dry biomass* (DM) (Patel et al. 1985; Xue et al. 2004).
- *LAI* as a key variable for estimating foliage cover, crop growth dynamics, and yield forecasting (Patel et al. 1985; Martin and Heilmann 1986; Xiao et al. 2002; Xue et al. 2004, 2005; Inoue et al. 2008).
- *Plant height* (Miyama and Sato 1985; Kurosu, Fujita, and Chiba 1995; Choudhury, Chakraborty, and Parihar 2007).
- *Green leaf chlorophyll density* (GLCD), which is of particular significance to precision agriculture, as an indicator of the photosynthesis activity that is related to the nitrogen nutritional level in green vegetation and serves as a measure of crop responses to nitrogen application.
- *Crop yield* (Patel et al. 1985; Fang et al. 1998; Bastiaansen and Ali 2003) as a key element for rural development and an indicator of national food security. Bastiaansen and Ali (2003) even assessed for the timely initiation of food trade to secure the national demand. Forecasting the crop area year-by-year, here is the key step to realize crop production forecasting (Fang et al. 1998).
- *Fractional photosynthetically active radiation* (fPAR) and *absorbed photosynthetically active radiation* (APAR) (Bartlett et al. 1988; Blackburn 1998; Inoue et al. 2008). The PAR value describes the total amount of radiation available for photosynthesis if leaves intercept all radiation (Bastiaansen and Ali 2003). Leaves transmit and reflect solar radiation; thus, only a fraction of PAR will be absorbed by the canopy (APAR) and used for carbon dioxide assimilation (Bastiaansen and Ali 2003). The fraction of PAR that is absorbed by a plant canopy (fPAR) has been shown to be

related to net primary productivity (NPP) as a function of an efficiency coefficient defining the carbon fixed per unit radiation intercepted (Blackburn 1998).
- *Plant water content* (Patel et al. 1985; Shibayama et al. 1993).
- *Final grain and straw* (Patel et al. 1985).
- *Nitrogen treatment* (Vaesen et al. 2001; Xue et al. 2004; Lee et al. 2008).
- *Water depth, water clarity, water background colour, plant chlorophyll content, and rice cultivar* (Vaesen et al. 2001).

A more advanced application of remotely sensed data is the modelling of crop growth. These models simulate the biophysical processes of an entire crop cycle, considering as many components from soil, atmosphere, and so on, as possible, to provide a continuous description of plant growth and development (Doraiswamy et al. 2004). Since such a model is developed on the basis of a functional relationship for a particular variety of variables in a particular environment (Tennakoon, Murty, and Eiumnoh 1992), its accuracy strongly depends on how representative the chosen set of variables is. Thus, models that use only one biophysical process that contributes to the final yield may not produce sufficient results (Doraiswamy et al. 2004). The incorporation of input parameters derived from remote sensing provides spatial integrity as a permanent calibration of the model parameters (Doraiswamy et al. 2004).

The role of crop models in combination with remote sensing is as follows: they

- allow a fast, non-destructive (Sims and Gamon 2002) and relatively cheap characterization of crop status (Bouman 1995);
- enable the use of model outputs (e.g. LAI, ground cover etc.) in growth simulation models (Vaesen et al. 2001);
- make spatial extrapolation to the regional level using satellite imagery feasible (Ishiguro et al. 1993); and
- make model results objective and repeatable (Vaesen et al. 2001).

3.1. Remote sensing of rice fields based on high- to medium-resolution optical data

Medium-resolution satellite sensors probably play the most important role in the discrimination of paddy fields. Data acquisition is rather cheap and the spatial resolution of rice fields is sufficient to discriminate between them; thus, it is possible to cover an entire cultivation area with a few scenes. Over 30 publications, with study areas in 13 countries, have been reviewed for this section.

The applied data were acquired from satellites of the Landsat, Système Pour l'Observation de la Terre (SPOT), and Indian Remote Sensing Satellite (IRS) series, ranging from 20 m spatial resolution from the SPOT sensors through 79 m from the Landsat Multi Spectral Scanner (MSS) to 188 m from the IRS Wide-Field Scanner (WiFS). The exception constitutes the application of data from the Japanese satellite MOS-1, with 50 m spatial resolution.

3.1.1. Application fields

The most common aim of the application of medium-resolution optical data is the delineation of paddy fields (McCloy, Smith, and Robinson 1987; Panigrahy and Parihar 1992; Ishiguro et al. 1993; Miyazato et al. 1993; Okamoto and Fukuhara 1996; Singh and Singh 1996; Fang 1998; Fang et al. 1998; Turner and Congalton 1998; Oguro et al. 2001; Van Niel et al. 2003). One of the first studies on this topic was conducted by McCloy, Smith, and Robinson (1987). They used Landsat MSS data to monitor rice growing areas over 2 years in New South Wales, Australia. Similarly, Turner and Congalton (1998) mapped rice fields in the Inner Niger Delta, Mali, with three SPOT-XS scenes from the same year. They found it difficult because of the small size of cropped fields, the resulting heterogeneity of the region, and the low vegetation cover within and outside the cropped areas. Landsat Thematic Mapper and MOS-1 data were applied by Ishiguro et al. (1993) for the rice area estimation in a region of Japan. Some confusion was caused by the small field sizes and shadowy tree canopy, resulting in some overlap with the city and forested areas.

A general land-cover classification with a focus on rice was conducted by Panigrahy, Ray, and Panigrahy (2009). They implemented a crop classification, including rice, groundnut, and vegetables, for the Cuttack district of Orissa state, India, on the basis of IRS-P6 advanced wide-field sensor (AWiFS) data.

Another common application of medium-resolution optical data is change detection (Yamagata et al. 1988; Laba, Smith, and Degloria 1997; Thiruvengadachari and Sakhtivadivel 1997; Okamoto, Yamakawa, and Kawashima 1998; Bailey et al. 2001; Son and Tu 2008). This can be a very useful tool to monitor and measure trends in the extent, composition, and state of paddy fields due to crop rotation, transformation of natural vegetation, or the damage caused by floods or storms. These can be detected by the classification of several scenes of the same area from different years or seasons and the subsequent comparison or mathematical subtraction of the images. Two studies that analysed land-cover change with Landsat Enhanced Thematic Mapper Plus (ETM+) data in comparison to digitized maps were conducted by Bailey et al. (2001) and Son and Tu (2008), and Bailey et al. overlaid the 1994 extent of digitized wild rice fields in Minnesota, USA, from aerial photographs with a 1999 Landsat ETM+ classification and discovered a 65% crop loss due to increased precipitation and the subsequent flooding of the potential fields. Son and Tu (2008) examined forestland conversion between 2001 and 2005 in the lower Mekong Delta, Vietnam, comparing 2001 ETM+ data with a 2005 land-use map. They discovered a dramatic loss of forestland of more than 70%, with the major part transformed into irrigated rice fields.

Other studies were undertaken with the aim of assessing the damage caused by floods, and so on, to paddy fields (Miyama and Sato 1985; Yamagata et al. 1988; Okamoto, Yamakawa, and Kawashima 1998; Bailey et al. 2001). Okamoto, Yamakawa, and Kawashima (1998), for example, estimated flood damage to rice production in North Korea in 1995. By the application of change detection between several Landsat TM scenes, it was estimated that 42% of the total area of rice fields in North Korea were affected by the floods.

Since rice fields are flood-irrigated during the growing seasons, they provide ideal breeding habitats for the malaria vector. Diuk-Wasser et al. (2006) used Landsat ETM+ data to identify and monitor rice-related malaria vector breeding habitats in an irrigated rice-growing area in Mali.

The crop residue burning and the resulting green-house gas emissions in a rice-growing area on the Indo-Gangetic Plains, India, were investigated by Badarinath et al. (2001) on the basis of IRS-P6 AWiFS data. The burnt area classifications and the subsequent estimation of emissions suggested that emissions from rice residue were relatively higher than those from wheat residues and that an incorporation of the residues into the soil should be preferred.

The estimation of rice yields is a further application of medium-resolution optical satellite data. Patel et al. (1991) used IRS 1-A LISS-I data and transformed Landsat MSS data to investigate the relation between spectral reflectances and yield data in two districts of

Orissa state, India. Tennakoon, Murty, and Eiumnoh (1992) delineated paddy fields on Landsat TM images for a study area in Thailand and subsequently related reflectance values with the yield information obtained by interviews of farmers. High correlations were derived and a yield estimation model was developed.

3.1.2. Methods

As the applied data and area covered vary from study to study, the processing methods used are also numerous. Manual digitization approaches or classifications based on single bands, band combinations, or vegetation indices (VIs) are utilized depending on the satellite data chosen as the basis. On the other hand, object-based methods, decision tree classifications, or other more complex methods on the basis of medium-resolution satellite data could not be found.

A very common approach on the regional scale is the visual interpretation and on-screen digitization of rice fields (Patel et al. 1991; Wood et al. 1991; Tennakoon, Murty, and Eiumnoh 1992; Ishiguro et al. 1993; Miyazato et al. 1993; Singh and Singh 1996; Fang 1998; Okamoto, Yamakawa, and Kawashima 1998). This can be an entirely manual digitization of field borders, visual selection of training areas for a subsequent supervised classification (Tennakoon, Murty, and Eiumnoh 1992; Miyazato et al. 1993), or visual analysis of spectral information for the determination of thresholds (Patel et al. 1991).

Furthermore, supervised and unsupervised classifications have been successfully applied for the mapping of paddy fields. For example, Fang (1998) investigated the use of unsupervised classifications of Landsat-5 TM data in Hubei Province, China. First, an unsupervised classification was conducted, and later, 10 major land cover categories were derived from it by comparison with different thematic maps. The accuracies of this method were fairly good, with 81% for semi-late rice and 90% for early rice. However, supervised classifications on the basis of ground truth training data are used more commonly, with generally higher accuracies. Diuk-Wasser et al. (2006) applied a supervised maximum likelihood classification (MLC) to Landsat ETM+ scenes in a rice-growing area in Mali. The use of a 12-band data set, merged from two scenes, one from the growing and one from the harvesting time, resulted in 98% accuracy for the delineation of rice. The importance of bands 3 and 4 (normalized difference vegetation index (NDVI)) and bands 5 and 7 (middle infrared) for this purpose was emphasized. In general, maximum likelihood is the most popular supervised classifier for detecting paddy fields with medium-resolution remote sensing (Miyama and Sato 1985; McCloy, Smith, and Robinson 1987; Panigrahy and Parihar 1992; Panigrahy et al. 1995; Barbosa, Casterad, and Herrero 1996; Panigrahy and Sharma 1997; Fang 1998; Turner and Congalton 1998; Badarinath et al. 2001; Van Niel et al. 2003; Panigrahy, Ray, and Panigrahy 2009).

In addition to the use of multi-date data, classification results are often improved by the application of prior image transformations of the input data. Panigrahy and Sharma (1997) conducted a principal component transformation of LISS-I data to optimize input data sets. This was further investigated by Panigrahy, Ray, and Panigrahy (2009) on the basis of AWiFS data. Another transformation, the minimum noise fraction transformation, was applied by Bailey et al. (2001). This was derived from a multi-date Landsat ETM+ data set for better identification of wet vegetation.

An important field of research is the employment of VIs, such as NDVI, enhanced vegetation index (EVI), LAI, or moisture stress index (MSI). Oguro et al. (2001) investigated the use of NDVI and EVI from different sensors linked to SAR data for the monitoring of rice fields. They concluded that a combination of NDVI and EVI is best suited to the purpose because the difference between these two can help to discriminate rice fields from forest, resulting in an error less than 2%.

Furthermore, Panigrahy, Ray, and Panigrahy (2009) tested a number of indicators such as NDVI, MSI, and the self-developed three-band index (TBI), consisting of NIR, red band, and shortwave infrared (SWIR), for crop discrimination and classification. In general, they concluded that the incorporation of the SWIR band, indicating stress due to water, in a VI for classifications increased the overall accuracy. Van Niel et al. (2003) focused on the usefulness of moisture-based indices and compared the rice classification results of the normalized difference infrared index (NDII), MSI, and the depth of ETM+ band 5 (SWIR) with NDVI and a standard MLC of all six reflective ETM+ bands. On the one hand, this study shows the importance of the implication of environmental moisture in the classification progress of rice fields, and, on the other hand, it shows the importance of choosing the right index, depending on the focus time of the growing cycle.

3.2. Remote sensing of rice fields based on low-resolution optical data

Low spatial resolution sensors such as the Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), and SPOT VEGETATION are also characterized by high temporal resolution and wide swath width, providing broad area coverage at a lower cost than high spatial resolution sensors (Kamthonkiat et al. 2005). The high temporal resolution is one of the most critical requirements for agricultural system analysis, capturing the dynamics of crop growth in a year (Panigrahy et al. 2005). A further motivation to use these low spatial resolution data is the dimension of the research area, which can be on a continental or even global scale due to the swath widths of approximately 2500 km for AVHRR, 2330 km for MODIS, and about 2200 km for SPOT VEGETATION. These broad-scaled studies commonly focus on the changing patterns of global land cover and the hypothetical linkages between these patterns, human activities, biogeochemical cycles, and climate (Bartlett et al. 1988).

3.2.1. Application fields

MODIS, aboard the Terra and Aqua satellites, views the entire Earth's surface every 1–2 days with 36 spectral bands and spatial resolutions of 250, 500, and 1000 m (Cheng 2006). The freely available data contain a set of scientific standard products, such as VIs. Thus, the sensor is an optimal tool to provide long-term integrated measurements of the land surface (Cheng 2006).

For example, Chen, Son, and Chang (2012) conducted a study in the Mekong Delta, focusing on the change in rice-cropping systems. They used a MODIS NDVI time series between 2001 and 2007, with a spatial resolution of 250 m. Their rice monitoring procedure included three steps: first, noise filtering using empirical mode decomposition (EMD), and then, an endmember extraction that was subsequently used for training in a linear mixture model for the classification. In a last step, the results were verified by comparison with ground truth and statistical data (Chen, Son, and Chang 2012). The overall accuracy of their classification was 90.1%.

Gumma et al. (2011) used an 8 day composite MODIS NDVI time series of 10 years (2000–2009) with 500 m spatial resolution to monitor changes in a rice-growing area in Nepal. First, they divided the study area into areas with steeper and less steep gradients based on Shuttle Radar Topography Mission (SRTM) data. Then, an isodata classification algorithm was applied, resulting in up to 100 classes depending on the segment. A series of additional data, such as ground truth data and very high resolution Google Earth images, was used for the class identification. In the end, they aggregated the unsupervised classes into 11 classes. The accuracies of the final maps were assessed by comparison with field plot data and the district-level rice area statistics of Nepal; these ranged between 67% and 91% for the various rice classes (Gumma et al. 2011). On the basis of these maps, a severe drought incidence in 2006 could be monitored by a decline of 13% in the rice cultivated area (Gumma et al. 2011).

The two MODIS VI products, NDVI and EVI, are produced globally at 16 day intervals in the above-mentioned spatial resolutions. The commonly known NDVI is chlorophyll-sensitive and responds mostly to variations in the visible part of the spectrum, while the EVI is more NIR-sensitive and is improved for high biomass regions (Cheng 2006). Thus, the two indices complement each other very well. Since VIs play a major role in monitoring rice growth, as already seen earlier, and MODIS provides a long-term time series for monitoring phenology, the MODIS VI products enjoy great popularity in vegetation research and in the monitoring of rice in particular (Cheng 2006).

The same applies for the AVHRR and SPOT VEGETATION sensors. Singh, Oza, and Pandya (2006), for example, used the NDVI derived from AVHRR data to investigate a shift in the temporal rice growth pattern in terms of emergence and peak vegetation. They observed an advance of the rice-growing pattern by 3–4 weeks in Punjab, India, from 1981 to 2000. Since the AVHRR NDVI data are not sensitive at the time of crop emergence, the passive microwave radiometer Special Sensor Microwave Imager (SSM/I) was used in addition. For SPOT VEGETATION, Kamthonkiat et al. (2005) employed a time series of VEGETATION NDVI data in combination with rainfall data to discriminate between irrigated and rainfed paddy rice fields in Suphanburi Province, Thailand. The up-to-date mapping of irrigated areas is very important for the improvement of water management, especially for the quantifying of water use. They correlated the peak NDVI with the average rainfall data. The results showed high correlations between peak rainfall and a single peak NDVI for a certain lag for rainfed rice and multiple peaks of NDVI for irrigated rice and subsequently, low correlations with rainfall.

Besides the application of VIs, low spatial resolution sensors are useful to map major land-cover classes. Panigrahy et al. (2005), for example, employed an unsupervised classification with a focus on agricultural areas classified on the basis of SPOT VEGETATION data in order to determine their cropping pattern and crop rotation. Three seasons were defined for the mapping of cropping patterns in Orissa state, India, and from them the crop rotation was derived. Thus, four different crop classes and seven crop rotation methods could be identified, although it has to be mentioned that a complete quality assessment has not yet been done.

3.2.2. Methods

Sakamoto et al. (2005) developed a new method for the detection of the phenological stages of paddy rice from MODIS data, called the wavelet-based filter for determining crop phenology (WFCP). The WFCP consists of three procedures. The one is the preprocessing of the satellite data. They decided to use the EVI since it has an improved atmospheric correction (Huete et al. 2002), which is important because the rice-growing season falls in the rainy season, which has high humidity. The index was derived from the 8 day global 500 m surface reflectance product for the year 2002 and pixels that were affected by thick clouds or broad-sensor zenith angles, resulting in low resolution, were removed. In the second procedure, the EVI time series was filtered by a wavelet transform that was found to be better than a Fourier transform. This was done in order to remove noise from the time series. In the third procedure, the different phenological stages, planting date, heading date, harvesting date, and overall growing period were determined (Sakamoto et al. 2005). For the heading date, the maximum EVI was used. For the estimation of the planting date, the minimal point or the inflection point earlier than 60 days from the estimated heading date was identified. The later one of these points was automatically taken as the planting date (Sakamoto et al. 2005). The inflection point later than 30 days after the estimated heading date was determined as the harvesting date (Sakamoto et al. 2005). The validation for 30 Japanese test sites showed RMSE values of growing period and phenological stages of about 12 days.

In a further study by Sakamoto et al. (2005), the developed WFCP method was applied for the Red River Delta. The results indicate the prevalence of a double rice-cropping system in the delta as well as winter-spring rice-cropping areas in the eastern part (Sakamoto et al. 2005).

A third study of the research group around Sakamoto et al. (2006) applied the WFCP in the Mekong Delta, focusing on the spatial distribution of the heading stage and the rice-cropping system adapted to seasonal changes in water resources between 2002 and 2003. For this purpose, they modified the original WFCP, removing the preprocessing step, which considers the sensor zenith angle. This was necessary because of the high precipitation during the rainy season. In addition, the threshold for noise rejection in the time series during the second procedure of the method was altered (Sakamoto et al. 2006). This adjust method was called the wavelet-based filter for evaluating the spatial distribution of cropping systems (WFCS). An analysis of annual changes in rice-cropping systems between 2002 and 2003 showed an expansion of triple-cropped rice into flood and salinity intrusion areas (Sakamoto et al. 2006). These results indicate a successful implementation of flood and salinity limitation by improved farming technologies and land management (Sakamoto et al. 2006).

Sakamoto et al. (2009b) published two more studies based on longer MODIS time series between 2000 and 2006 and between 2000 and 2008, respectively. In addition to the previously used methods, WFCP and WFCS, a third method, the wavelet-based filter for detecting spatio-temporal changes in flood inundation (WFFI), was introduced to estimate the start and end dates of flood inundation on the basis of the land surface water index time series and EVI. By the application of this method, they were able to show a steady expansion of farmland and a shift from double rice-cropping systems to triple rice-cropping systems in the Mekong Delta (Sakamoto 2009; Sakamoto et al. 2009b). This was possible due to infrastructure improvements, such as ring-dike constructions and water resource infrastructure (Sakamoto 2009).

Although low-resolution remote sensing is recognized as a useful tool in crop monitoring at a global scale (Kamthonkiat et al. 2005), the end user at the regional level needs a higher resolution in order to draw precise conclusions concerning, for example, yield estimation and forecast. The coarse resolution of AVHRR, MODIS, or VEGETATION is just not accurate enough to give a good impression of the field scale situation but is rather intended to give an overview of the general situation in the area. However, the rather small number of publications in this field of research may indicate that the usage of low-resolution data is still expandable.

Some studies try to overcome the problem with coarse spatial resolution using higher resolution data as a link to the AVHRR or VEGETATION data (Bartlett et al. 1988; Quarmby et al. 1993; Fang et al. 1998). Fang et al. (1998), for example, estimated the rice area in Hubei Province, China, from AVHRR data by using higher resolution Landsat TM data. By linking the data with a linear statistical model, they used AVHRR data to forecast the rice area of another year. Since higher resolution data are still necessary for these methods, the benefit of the integration of low-resolution data seems questionable.

3.3. Remote sensing of rice fields based on hyperspectral data

The development of hyperspectral sensors to precisely measure spectral reflectance or emittance created opportunities to quantitatively describe agronomic parameters and to understand the effect of different influences on the phenology of vegetation (Hatfield et al. 2008).

Hyperspectral remote sensing in the mapping of rice has been applied in a series of publications. For this review, we examined more than 70 publications, the majority about the use of the field spectroradiometer. Both field and air-/spaceborne sensors have a broad range of narrow spectral bands in the visible and NIR regions between 400 and 2500 nm. The advantage of air-/spaceborne sensors is, of course, a wide and consistent spatial coverage compared to the point data of the field spectroradiometer. On the other hand, the spaceborne sensors especially have to go through a long series of preprocessing for the correction of atmospheric and geometric effects. This issue is still a major subject in the literature, especially for the spaceborne sensors (McVicar 2005). Thus, airborne and spaceborne sensors are, so far, primarily used for the mapping of rice and their cropping systems, while studies based on field spectroradiometers focus on more complex biophysical variables.

3.3.1. Field spectroradiometer derived data

Spectral data from the current medium-resolution spaceborne satellites have limitations in providing accurate estimates of the biophysical characteristics of agricultural crops (Wiegand et al. 1991; Thenkabail, Smith, and De Pauw 2000). In order to get a precise impression of the spectral and, hence, biophysical characteristics of crops, a hyperspectral analysis directly at the plant in a field or laboratory situation is essential.

In the research on rice crops, the main applications of hyperspectral field data are:

- rice growth estimation and prediction, for example (Yang and Su 1998; Yang and Chen 2004);
- estimation of rice yields, for example (Wiegand et al. 1989; Shibayama and Akiyama 1991; Inoue, Moran, and Horie 1998);
- nutrient and fertilizer management, for example (Patel et al. 1985; Xue et al. 2004; Chang, Shen, and Lo 2005);
- insect infestation and pest management (Yang and Cheng 2001; Yang, Cheng, and Chen 2007); and
- irrigation management and water stress (Shibayama et al. 1993; Xue et al. 2005).

A general task in the hyperspectral remote sensing of crops is the determination of narrowbands that are best suited for characterizing biophysical variables. The challenge in the analysis of remotely sensed data for biophysical parameters is that the reflectance of a vegetative canopy is determined not only by plant morphology and phenology but also by soil characteristics, for example, soil type or brightness, irradiation, observation angle, and atmospheric conditions (Vaesen et al. 2001). In addition, the spectral reflectance of paddy rice may be influenced by floodwater, which prohibits the unconditional application of VIs for monitoring rice (Vaesen et al. 2001). In order to overcome the problem of soil and water background effects, narrowbands, soil-adjusted vegetation indices (SAVIs), band ratios, and estimations of crop characteristics are employed. The identification of the best hyperspectral bands and the determination of their optimal number, especially in the visible and NIR portion of the spectrum, are required to reduce the redundancy in hyperspectral data (Thenkabail, Smith, and De Pauw 2000). Thenkabail, Smith, and De Pauw (2000) found strong relationships with crop characteristics in the red (650–700 nm), in the shorter wavelengths of green (500–550 nm), and in the NIR (900–940 nm and centred at 982 nm) sections of the spectrum. The decision for the best bands and band combinations is strongly based on several variables, such as crop condition, crop growth stage, and cultural practices (Thenkabail, Smith, and De Pauw 2000).

In the literature, the optimal bands are most commonly identified using the means of multiple regression analysis, searching for a linear relationship between spectral information and different crop biophysical variables (Thenkabail, Smith, and De Pauw 2000). Shibayama and Akiyama (1991) showed that stepwise multiple regression models performed on narrowbands provide flexibility in choosing the bands that comprehend maximum information during the different stages of crop growth (Thenkabail, Smith, and De Pauw 2000). With varying crop conditions because of factors such as management conditions, soil characteristics, climatic conditions, and cultural practices, different band combinations are used (Thenkabail, Smith, and De Pauw 2000).

- *LAI estimation from field reflectance measurements*. Shibayama and Akiyama (Shibayama and Akiyama 1989) discovered the highest correlations with LAI in the visible bands, with the highest correlation observed for the 480 nm band over the entire growing season. They also tested two-band indices and found the correlations of the ratio $R_{840\text{nm}}/R_{560\text{nm}}$ ($r = 0.825$) to be the best (Shibayama and Akiyama 1989). The correlations between LAI and this ratio, observed by Shibayama and Akiyama (1989), were superior to the single-band correlations.
- *Biomass estimation from spectral reflectance*. This was derived more precisely than LAI in the study conducted by Casanova, Epema, and Goudriaan (1998). The same was determined by Shibayama and Akiyama (1989), who achieved good results with the difference between reflectances at 1100 and 1200 nm and the difference between reflectances at 1100 and 1650 nm to estimate biomass until heading. Furthermore, Takahashi et al. (2000) predicted dry weight biomass from visible and NIR reflectances of rice canopies. Since dry weight biomass greatly influences rice yield and grain quality, it is important to monitor this parameter before the heading stage in order to optimize manure practice (Takahashi et al. 2000).
- *Simple band ratios*. Simple band ratios like the one Shibayama and Akiyama (1991) used to estimate LAI (see above) were applied in several studies. Chang, Shen, and Lo (2005), for instance, used two multiple regression models consisting of band ratios (NIR/red and NIR/green) to estimate rice yields. These indices were highly correlated with grain yield and the derived regression equations are said to have the potential to predict the yield for future years (Chang, Shen, and Lo 2005).
- *VIs*. Common VIs like NDVI have been calculated from rice crop reflectance as well as less frequently used VIs such as SAVI, ratio vegetation index (RVI), perpendicular vegetation index (PVI), and weighted difference vegetation index (WDVI) (Casanova, Epema, and Goudriaan 1998; Nguyen and Lee 2006). WDVI and PVI, which are corrected for soil reflectance, are more linear and have less scatter in the fPAR models applied by Casanova, Epema, and Goudriaan (1998) than NDVI and PVI. In the study conducted by Casanova, Epema, and Goudriaan (1998), all models of VI fit better in the vegetative and pre-heading stage than in post-heading because of senescence effects. Yang and Chen (2004) confirmed this observation and suggested the separation of the growing period in the pre- and post-heading stages for the modelling of growth parameters. Several authors (Casanova, Epema, and Goudriaan 1998; Yang and Su 1998; Yang and Chen 2004) accordingly come to the conclusion that NDVI should not be used in the early development stages due to the strong background

effects as well as in the late post-heading stages due to senescence effects and the developing panicle.

- *fAPAR*. This parameter is often used as a key variable in simple process models and was found to be well correlated with VIs (Casanova, Epema, and Goudriaan 1998; Inoue, Moran, and Horie 1998). Casanova, Epema, and Goudriaan (1998) directly derived fAPAR values from VIs based on a physical reflectance model. Both Casanova, Epema, and Goudriaan (1998) and Inoue, Moran, and Horie (1998) observed VI to be less sensitive to fAPAR for fAPAR values larger than 0.4.
- *Photosynthetic variables*. For the estimation of photosynthetic variables, such as radiation-use efficiency and photosynthetic capacity, Inoue et al. (2008) explored simple normalized difference spectral indices (NDSIs) based on season-long measurements of hyperspectral canopy reflectance, ecosystem CO_2 flux, as well as plant and micro-meteorological variables. They tested all possible hyperspectral band combinations between 350 and 2500 nm for their correlation with a couple of photosynthetic variables, including fAPAR and gross primary productivity (GPP). They found several new indices, some of them being much more effective than conventional indices such as NDVI or photochemical reflectance index (PRI) (Inoue et al. 2008). For instance, NDSI[550, 410] and NDSI[720, 420] exhibited linear relationships with fAPAR for the entire growing season without any phenological dependence (Inoue et al. 2008).

3.3.2. Application fields

3.3.2.1. Nutrient and fertilizer management. The estimation of grain yield and yield components in the literature is often coupled with the analysis of time and amount of N fertilizer application or leaf nitrogen content estimation (Inoue, Moran, and Horie 1998; Takahashi et al. 2000; Nguyen and Lee 2006; Zhang et al. 2006). In this context, various models have been employed in order to predict rice yield from indicators related to N status before the heading stage (Nguyen and Lee 2006). Based on earlier studies emphasizing a close relationship between chlorophyll or nitrogen content and the spectral transmittance of plant leaves (Inada 1985), Inoue, Moran, and Horie (1998) found a close linear relationship between the spectral ratio $R_{830\mathrm{nm}}/R_{550\mathrm{nm}}$ and leaf nitrogen content after the heading stage. On the basis of the paddy field regarded as a big leaf, this ratio seemed to be an effective indicator for the estimation of leaf nitrogen content (Inoue, Moran, and Horie 1998). For the estimation of the total amount of leaf nitrogen, Inoue, Moran, and Horie (1998) applied a combination of four spectral bands: $R_{550\mathrm{nm}}$, $R_{830\mathrm{nm}}$, $R_{1650\mathrm{nm}}$, and $R_{2200\mathrm{nm}}$.

Zhang et al. (2006) investigated the relationship between N supply and canopy spectral reflectance and found significant differences in the N concentrations of canopy leaves at different growth stages. They determined a close relationship between the N status of rice and the visible and NIR ranges of the spectrum, and subsequently used NDVI and RVI to predict the N status of rice (Zhang et al. 2006). Xue et al. (2004) conducted a very similar study relating seasonal canopy reflectances, different band ratios, and NDVI with N concentration and accumulation in rice leaves under different N treatments. They found the ratio between NIR and the green band ($R_{810\mathrm{nm}}/R_{560\mathrm{nm}}$) to be especially linearly related to N accumulation across the entire growth period and independent of the N treatment level. Thus, this band ratio was suggested for the monitoring of N status in rice plants (Xue et al. 2004).

Lee et al. (2008) applied an even simpler spectral index (SI), consisting of the first derivative of canopy reflectance at 735 nm, for the assessment of N status in rice plants. They found close linear relations for the panicle initiation stage.

3.3.2.2. Insect infestations and pest management. In addition to various parameters such as N treatment and crop growth stages, weeds and pest infestations produce spectral interferences, resulting in difficulties in spectral discrimination between species (Yang, Cheng, and Chen 2007). Especially, the brown planthopper, *Nilaparavata lugens*, is considered to be a serious insect pest in many rice-producing regions, inflicting severe damage to rice crops each year (Yang and Cheng 2001). Effective control of these insects is a difficult task for rice farmers (Yang and Cheng 2001). Yang and Cheng (2001) and subsequently Yang, Cheng, and Chen (2007) investigated the relationship between spectral characteristics and symptoms of infestation of the Brown Planthopper and another widely distributed pest, the rice leaffolder, *Cnaphalocrocis medinalis*. Linear correlations between spectral reflectance and scale of infestation for single bands and band ratios were conducted (Yang, Cheng, and Chen 2007). Canopies infested with brown planthopper had the highest correlation coefficients at 426 nm ($r = 0.878$) and the highest determination coefficients for the band ratio $R_{\mathrm{NIR}}/R_{\mathrm{red}}$ ($R^2 = 0.922$) (Yang, Cheng, and Chen 2007). Leaffolder-infested canopies showed negative and more diverse correlations depending on the growth stage of the rice plants.

The analysis of hyperspectral data offers a better understanding of field conditions and the interactions of pests such as insects and fungi with plants for site-specific pest management (Kobayashi et al. 2001; Yang, Cheng, and Chen 2007). It can furthermore help to improve the timing of pesticide application as well as the estimation of the necessary amount (Kobayashi et al. 2001; Yang, Cheng, and Chen 2007).

3.3.2.3. Irrigation management. The damage caused by droughts is a major problem in paddy rice cultivations, especially under rainfed conditions (Shibayama et al. 1993). Remote sensing can improve the monitoring of water stress and drought damage and subsequently contribute to efficient water application management (Shibayama et al. 1993). For this purpose, Shibayama et al. (1993) investigated the spectral determination of changes in soil water content and furthermore the physiological changes of rice plants due to water deficits. They found the NIR and mid-infrared ranges (1190–1320 nm and around 1600 nm) to be highly sensitive to water and soil background surfaces even under dense canopy cover (Shibayama et al. 1993). However, this sensitivity is caused by the water background itself and is not due to physiological changes in rice canopies (Shibayama et al. 1993). In order to detect the water status of canopies, they used the first derivative of the canopy reflectance spectrum, which removes background effects (Shibayama et al. 1993). The derivative at 960 nm was found to be best suited for the purpose; it detected water-stressed canopies before symptoms were visible and before the NDVI did (Shibayama et al. 1993).

Song et al. (2011) conducted another study investigating the spectral reflectance of water-stressed paddy rice. They found the bands at 1158, 1378, and 1965 nm to be the most useful in order to diagnose stress conditions across three different irrigation levels (Song et al. 2011). However, according to the authors, the accuracies of this three-band regression are rather poor ($R^2 = 0.75$) because of the water loss of leaf samples during the measurement experiment (Song et al. 2011).

3.3.2.4. Heavy metal pollution. Rapid industrial development has caused many environmental problems in emerging countries such as China. One of the major problems is the contamination of soils with heavy metals, which can end up in agricultural crops, posing a serious health threat (Liu et al. 2011). Liu et al. (2011) investigated the use of different indicators derived from hyperspectral data for the detection of rice stress with heavy metal pollution. They found the red-edge position (REP) to be the most sensitive indicator for this purpose, with a shift of 3 and 6 nm towards the short wavelength depending on the level of pollution (Liu et al. 2011).

3.3.3. Airborne and spaceborne hyperspectral data

In order to cover larger areas, the methods from hyperspectral field research have to be transferred to airborne or spaceborne platforms. Although it provides great potential for the analysis of paddy rice fields, hyperspectral remote sensing from airborne and spaceborne sensors is not very well represented in the literature. This is probably due to the high costs of data and the fact that only one to two spaceborne hyperspectral sensors exist so far.

3.3.3.1. Airborne. LaCapra et al. (1996) used the airborne hyperspectral sensor airborne visible/infrared imaging spectrometer (AVIRIS) to analyse the foliar chemistry of several rice fields in California, USA. They applied a stepwise multiple linear regression to predict nitrogen and lignin concentrations from the reflectance spectra transformed as the first difference of absorbance. They could not derive statistically significant calibration equations for the lignin concentration in rice plants (LaCapra et al. 1996). Since lignins are a heterogeneous class of phenolic polymers with a high diversity of chemical forms and their measured concentrations were in general rather small, these results were not surprising (LaCapra et al. 1996). On the other hand, they proved that airborne hyperspectral data can be used to predict the nitrogen concentration of paddy rice fields, although they could not derive a general calibration equation since their multilevel relational data (MLR) tests were based on different sets of wavelengths for different subsets of the data (LaCapra et al. 1996).

Ryu, Suguri, and Umeda (2011) also used an airborne hyperspectral sensor, the AISA Eagle, to investigate the nitrogen concentration of rice plants at an experimental site in Japan. However, they specifically focused on the nitrogen concentration of multiple years at the heading stage, since the quality and quantity of rice grains are said to be closely related to the nitrogen status of the plant at this stage (Ryu, Suguri, and Umeda 2011). They tested models with different time spans, one to three years, based on MLR and partial least square regression (PLSR). The results indicate that PLSR models are more sensitive to nitrogen concentration at the heading stage, especially for multiple years (Ryu, Suguri, and Umeda 2011).

3.3.3.2. Spaceborne. A group of researchers from Australia's national science agency, the Commonwealth Scientific and Industrial Research Organisation (CSIRO), part of the Earth Observation-1 (EO-1) Science validation team, investigated the use of the Hyperion sensor for different agricultural applications in an Australian irrigation district and the effort of preprocessing the reflectance data. Hyperion provides a 30 m spatial resolution and, so far, offers the highest spectral resolution of all spaceborne sensors with 220 bands. The results of the CSIRO research group were released in a series of publications (Datt 1998; Jupp et al. 2003; McVicar 2005).

Datt et al. (2003) analysed a time series of six Hyperion images for yield estimation in the above-mentioned Coleambally irrigation area, Australia. They derived three SIs from the data, NDVI, the red-edge first derivative value (dRE), and REP and correlated these with spatial yield data for nine rice fields. Additional data included airborne hyperspectral HyMap images for validation and calibration purposes. The results show a high variability of correlation between different dates and paddy fields, indicating the influences of several factors, such as background water in the early developing stages and evergreen weeds in the later growth stages. Overall, the results outline the usefulness of dRE and REP for the yield estimation of rice, while NDVI mostly provided poor correlations with yield data (Datt et al. 2003).

Since the other publications by the CSIRO group (Datt 1998) primarily describe the methodology of preprocessing Hyperion data from an irrigation test site, they are only mentioned at this point and not discussed any further. McVicar (2005) concluded from his research that hyperspectral remote sensing, especially spaceborne, still needs a lot of research before it can become an operational tool for the rice industry. He sees the main fields of research in the parameters driving crop yield as well as the indirect and direct modelling of water use (efficiency) (McVicar 2005).

3.4. Remote sensing of rice fields based on radar data

The major advantage of radar data over optical data is the independence from clouds and solar illumination (Chakraborty, Panigrahy, and Sharma 1997). Since rice production in Southeast Asia occurs mainly under monsoon conditions and the skies outside the monsoon season are also often covered with haze and high-level clouds, the application of radar images becomes even more important for the monitoring of an entire crop cycle (Chen and McNairn 2006).

A wide range of research articles has proved the usefulness of SAR data for the mapping of rice paddy extent and the biophysical characteristics of rice. The temporal variation in radar backscatter over the growing season is the key for the delineation of rice fields (compare also Chapter 2.2) (Aschbacher et al. 1995; Le Toan et al. 1997; Ribbes and Le Toan 1999; Inoue et al. 2002; Chen and McNairn 2006).

3.4.1. Application fields

Mapping and monitoring (Aschbacher et al. 1995, Kurosu, Fujita, and Chiba 1995; Kurosu, Fujita, and Chiba 1997; Le Toan et al. 1997; Liew et al. 1998; Ribbes and Le Toan 1999; Holecz et al. 2000; Chen and McNairn 2006; Chen et al. 2007; Chen, Lin, and Pei 2007; Lam-Dao et al. 2007; Tan et al. 2007; Bouvet et al. 2009; Shen et al. 2009). The beginning of a crop cycle in an irrigated system is scheduled according to the water distribution scheme, which makes the crop calendar for different groups of fields highly variable (Le Toan et al. 1997). Le Toan et al. (1997) observed a shift of up to 6–8 weeks between fields within a given region in Indonesia. This shift results in differences in planting dates and subsequently in crop growth, which, as a consequence, ends in significant variations in the radar backscatter (Chen and McNairn 2006). These local variations in crop growth between different groups of fields cause difficulties in the mapping of rice fields by SAR imagery (Chen and McNairn 2006). Le Toan et al. (1997) found that the identification of rice fields cannot be conducted properly by employing standard classification methods based on the similarity in the image intensity of rice fields. They proposed a so-called temporal change measurement method for the mapping of rice fields based on the temporal variation of the SAR signal in order to cope with interfield differences (Le Toan et al. 1997; Chen and McNairn 2006). Liew et al. (1998) classified the rice-cropping systems in the Mekong Delta, Vietnam, in a similar approach, using a change index of the backscattering coefficient of ERS-2 SAR images. First, a composite map with 243 possible change classes was generated on the basis of change index maps classified with a 3 db threshold. These classes were then aggregated into thematic categories of rice-cropping systems using two different methods: a visual interpretation and a semiautomatic hierarchical clustering algorithm (Liew et al. 1998). Almost at the same time, Ribbes and Le Toan (1999) also applied a mapping approach based on the temporal change of backscatter in RADARSAT-1 data. The results were compared to available maps and found to have an accuracy of 87%.

Chen and McNairn (2006) made use of the above-mentioned interfield variations and developed an operational rice crop monitoring system based on these variations applied to a neural network classification in order to map rice production areas, to monitor rice growth, and to predict rice yields (Chen and McNairn 2006). They tested the usefulness of three approaches: an MLC, a change detection derived from simple image ratios and classified with a 3 db threshold as in Liew et al. (1998), and a neural network method. Although the latter provided the best results, they combined change detection with the neural network method for the monitoring system since neural networks require extensive and representative training data. Thus, their final monitoring system derives training data from the results of the change detection (Chen and McNairn 2006).

Two rather complex methods were conducted by Chen et al. (2007) and by Tan et al. (2007). The first used a Wishart distribution-based multi-temporal classifier on Environmental Satellite (ENVISAT) Advanced Synthetic Aperture Radar Alternating Polarization System (ASAR APS) data for rice mapping in Jiangsu Province, China. As done by Chen and McNairn (2006), the results were also compared to those from common classifiers and found to have the highest accuracies. Tan et al. (2007) developed a combined entropy decomposition and support vector machine (EDSVM) method using RADARSAT-1 data from three dates for a study area in Malaysia. This could bring a significant improvement compared to maximum likelihood based results.

Contrary to these approaches, Kurosu, Fujita, and Chiba (1997) used a rather simple classification approach of the ERS-1 C-band SAR data for the delineation of rice fields in Akita, Japan. They performed an MLC on principal component images, derived from six multi-temporal SAR images and achieved high accuracies (90%) in comparison to land-use survey data.

A commonly used method for the mapping of paddy fields is the application of polarization ratios (Chen, Lin, and Pei 2007; Lam-Dao et al. 2007; Bouvet et al. 2009). Chen, Lin, and Pei (2007) tested various ratio combinations of ENVISAT ASAR images polarized in HH and HV from different dates in 2006 for Guangdong Province, China. They found that the ratio between an HV image on 4 April and an HH image on 4 July provided the highest classification accuracy. It was stated that a simple threshold, in this case at 7 dB, could be used on the ratio image to highlight rice fields. Lam-Dao et al. (2007) also used ENVISAT ASAR ratios, but from a single date in the middle of the crop cycle in February 2007 for test sites in the Mekong Delta. In their approach, a pixel was classified as rice if two thresholds were valid: HH/VV $>$ 3 dB and $\sigma°$ of VV $<$ –7 dB. Thus, a maximum difference of 7% was achieved between classification results and agency statistical data. Bouvet et al. (2009) enhanced this HH/VV polarization ratio of ENVISAT data based on knowledge of the polarization behaviour of the rice canopy (compare Chapter 2.2).

Yield estimation (models) (Shao et al. 1999; Chen and McNairn 2006; Salas et al. 2007; Shen et al. 2009). The estimation of yields is often the final goal after the successful mapping of rice fields. Chen and McNairn (2006) used their classification results (mentioned above) as an input for yield prediction. In addition, they collected two sets of yield data, one by sampling and one by the estimation of farmers. After the removal of outliers, resulting from the discrepancy between these two data sets, the remaining field plots were used for training a further neural network. The obtained results showed an encouraging 94% prediction accuracy (Chen and McNairn 2006). Further yield prediction approaches were conducted by Shen et al. (2009) using the ORYZA2000 model with a rather high overestimation of 13%; by Salas et al. (2007) using the modified DNDC (denitrification–decomposition) model without validation of accuracy; and by Shao et al. (1999) using their own yield model based on three images from different stages of the crop cycle and claiming to have an accuracy of 91%.

Estimation and relationship of backscatter coefficients and rice growth parameters (Bouman 1991; Ribbes and Le Toan 1999; Choudhury, Chakraborty, and Parihar 2007; Chen et al. 2009). Radar backscatter was found to be strongly correlated to key growth parameters, i.e. crop age, plant height, and biomass (Kurosu, Fujita, and Chiba 1995; Le Toan et al. 1997; Ribbes and Le Toan 1999; Inoue et al. 2002; Choudhury, Chakraborty, and Parihar 2007). Kurosu, Fujita, and Chiba (1995) found that correlation coefficients between the averaged $\sigma°$ and the plant height, net weight, or plant moisture content of rice crops was higher than 0.9, proving their close relationships.

Choudhury, Chakraborty, and Parihar (2007) used the backscatter signal of RADARSAT-1 and ENVISAT related to plant height to estimate the transplantation date. Furthermore, the analysis of the temporal profile resulted in a relationship between peak backscatter value and peak vegetative stage. Similar to the studies described above, they also used a polarization ratio linearly related to fresh biomass. On the basis of these findings and using a hierarchical decision rule algorithm, rice-growing areas were mapped with an accuracy of 94.8% (Choudhury, Chakraborty, and Parihar 2007).

Kim, Hong, and Lee (2008) related different frequencies and polarizations to growth stages (compare Chapter 2.2 and Figure 7) and growth parameters. Biomass was correlated with L-band HH polarization at a large incident angle. Grain weight, which ultimately stands for grain yield, was best correlated with backscattering coefficients with X-band VV polarization at a large incident angle (Kim, Hong, and Lee 2008). Furthermore, the X-band was found to be sensitive to grain maturity during the post-heading stage (Kim, Hong, and Lee 2008).

Another important growth parameter is LAI; Kim, Hong, and Lee (2008) found it to be highly correlated with C-band HH- and cross-polarizations at high incident angles. Inoue et al. (2002) also analysed the interactions between microwave backscatter signatures and various plant variables, especially LAI for the entire crop period. They, on the other hand, found very high correlations with LAI at lower incident angles for the C and L bands and a decreasing correlation trend towards higher incident angles (Inoue et al. 2002). Kim, Hong, and Lee (2008) explained this discrepancy between their results with differences in crop structure, backscattering situations (e.g. roughness, moisture), crop types, and weather conditions. However, these differences show the difficulties of backscatter research even under experimental field conditions.

A further study investigating the relationship between LAI and rice backscatter was conducted by Chen et al. (2009). They correlated a VV/HH polarization ratio from ENVISAT ASAR data with field-measured LAI and found good results that could be used to estimate the LAI of rice-growing areas.

3.4.1.1. Comparing data applicability of different SAR data. Le Toan et al. (1997) and, in the following, Ribbes and Le Toan (1999) investigated the general applicability of RADARSAT-1 and ERS-1 data for the mapping and monitoring of rice fields. In general, the dynamic range of RADARSAT-1 data was found to be lower than that of ERS-1 data, resulting from a higher backscatter at HH than at VV polarization at early stages (Ribbes and Le Toan 1999). The comparison of the two different modes of RADARSAT-1 showed promising results from the fine-resolution F3 mode for the mapping of rice fields due to an earlier saturation level of $\sigma°$ (Ribbes and Le Toan 1999). However, since the RADARSAT-1 data saturate at a corresponding plant height of only 60 cm and a level of biomass of 1000 gm^{-2}, it was found to be rather unsuitable for the monitoring of the crop cycle (Ribbes and Le Toan 1999). This is the field of application for which ERS-1 data had an advantage over RADARSAT-1 data.

3.4.1.2. Evaluation of classification methods. As illustrated in the previous sections, numerous different methods have been applied for the mapping and monitoring of rice fields on the basis of radar data. One of the most commonly used classifiers, the MLC, was found to be rather unsuited for this purpose by several authors and was often applied as a reference in order to underline the quality of their customized methods (Chen and McNairn 2006; Chen et al. 2007; Chen, Lin, and Pei 2007; Tan et al. 2007). Chakraborty and Panigrahy (2000), for example, stated that MLC is not well suited to the multi-date data sets used in their study due to the large variability, which results in a large proportion of unclassified pixels. Panigrahy et al. (1997) had already conducted a study in 1997 based on an MLC that led to major misclassifications of rice with waterbodies like rivers, streams, and flooded fallow fields. Le Toan et al. (1997) came to the conclusion that no standard classification method provides acceptable results. Either each area has to be considered individually on the basis of certain variables, such as crop calendar, or different and more robust methods have to be applied. Particularly, the differences in planting dates create interfield differences in crop growth and, subsequently, large variations in radar backscatter, which cannot be covered well by MLC and similar methods (Le Toan et al. 1997). However, it has to be mentioned again that Kurosu, Fujita, and Chiba (1997) (see above) achieved good results with an MLC based on principal component images.

The classifier that was suggested by Chakraborty and Panigrahy (2000) instead of the MLC is a decision rule-based classifier (DRB) using logical and mathematical conditions to classify a pixel. On the basis of this method, the growth characteristics of different rice areas can be taken into account, and thus, it is well suited to handle the high variability in radar backscatter (Chakraborty and Panigrahy 2000).

Further applications are:

- mapping and modelling of greenhouse gas emissions from rice paddies with radar (Salas et al. 2007);
- relationship of irrigated rice growth and malaria vector breeding (Diuk-Wasser et al. 2006);
- discrimination of rice crop grown under different cultural practices (Chakraborty, Panigrahy, and Sharma 1997; Le Toan et al. 1997);
- rice crop inventory and acreage (Premalatha and Rao 1994; Aschbacher et al. 1995; Patel et al. 1995; Panigrahy et al. 1997; Chakraborty and Panigrahy 2000);
- characterization of agro-ecosystems (Choudhury et al. 2006); etc.

4. Discussion

In this article, we presented the basics of remote sensing-based mapping of rice cropped areas as well as numerous studies on this topic. The sensors used for this mapping vary with the application field of the study. The most common purpose is simply the delineation of rice paddies in order to assess the total coverage. A change detection, based on multiple classified images, is necessary for the monitoring and measuring of trends over growing seasons of several years. This is furthermore used for the discrimination of irrigated and rainfed rice as well as for the identification of other cultural practices. In addition, special applications, such as the identification of malaria vector breeding habitats, the identification of residue burning and the resulting greenhouse gas emissions, and the estimation and modelling of rice yields are conducted on the basis of airborne and satellite remote sensing. Applications that focus on the finer details of spectral information such as nutrient and fertilizer management or water stress detection are so far preferably carried out using field spectroradiometers.

Each application has specific requirements that have to be met by a suitable sensor. For example, the availability of data is a major issue. Hyperspectral data require substantial preprocessing (geometric and atmospheric correction) from experts, which leads to difficulties in providing a product for rice management on time (McVicar 2005). Furthermore, airborne hyperspectral data need considerable acquisition time, including the planning and conducting of the flight campaigns that can be delayed by bad weather conditions. Thus, McVicar (2005) sees hyperspectral remote sensing still more as a field of research than as an operational management tool for the rice industry. On the other hand, radar data are better suited for rice mapping in tropical and sub-tropical regions due to their independence of weather conditions. Since a major part of the growing season coincides with the rainy period, the availability of cloud-free spectral data is often low (Liew et al. 1998).

A further issue that defines the sensor used for a study are the involved costs. Especially, airborne hyperspectral data are very cost-intensive and can easily exceed the budget for a rice monitoring system on a regular basis. On the other hand, a lot of remote-sensing data are freely available these days, and the prices of medium to high-resolution satellite data are reasonable. Thiruvengadachari and Sakhtivadivel (1997), who used Landsat MSS, Landsat TM, and LISS-I data when these sensors were still fee-based, stated that remote-sensing data can be applied cost-effectively in order to improve agricultural production and productivity. Furthermore, the application costs were said to be less than 1% of the annual operation and maintenance costs for irrigation schemes in India (Thiruvengadachari and Sakhtivadivel 1997). With the improvement and automation of process chains, it should still be possible to lower these costs.

Further issues that are defined by the application are the spatial and temporal resolution of remote-sensing data. Depending on the scale of rice mapping and monitoring from field to global level, different spatial resolutions are advisable, which further affects the temporal resolution possible. The partially antagonistic behaviour of spatial and temporal resolution is a commonly known issue in the literature and shall not be discussed any further at this point. In general, it was found necessary to use multi-temporal observations for the proper mapping of paddy rice as well as for other applications (e.g. Liew et al. 1998). One reason for this is the varying start of the crop cycle, depending on the water distribution scheme. Thus, the beginning of crop cycles can differ across several weeks between fields within a region, resulting in a shift in phenology (Le Toan et al. 1997). On the one hand, it can be important to acquire spectral data from a certain growth stage, that is, several authors used data from the pre-transplanting or harvesting stage, offering windows of spectral contrast to the surrounding vegetation (Tennakoon, Murty, and Eiumnoh 1992; Turner and Congalton 1998; Diuk-Wasser et al. 2004). On the other hand, several spectral data sets are required to monitor rice development over an entire cropping season (Panigrahy et al. 1995). Either way, a multi-temporal analysis is necessary to determine the timing of the different growth stages if there is no additional information involved. Another issue increasing the need for multiple data sets is the frequent cloud coverage during the growing season, constraining the data quality.

For the discrimination between rice and non-rice areas on the basis of radar data, the analysis of multi-temporal data from the beginning of the crop cycle or even from the pre-transplanting stage is crucial too. Prior to transplanting, the backscatter difference between the flooded paddies and its surrounding non-flooded areas is very high, resulting in an easy delineation of rice fields (Chen and McNairn 2006). Furthermore, the most backscatter variation within paddy rice occurs during the first 48 days of the growing cycle, stressing the importance of multi-date data acquisition during this time (Ribbes and Le Toan 1999).

Concerning the methodology for the mapping and monitoring of rice fields, the applied procedures depend strongly on the used sensor. For medium- and low-resolution optical data, the MLC is the most common approach (compare Chapter 3.1). In some studies, a preprocessing of the input data (e.g. principal component analysis and minimum noise fraction) was conducted prior to the classification (e.g. Bailey et al. 2001; Panigrahy, Ray, and Panigrahy 2009). Furthermore, standard VIs, such as NDVI and EVI, as well as moisture-based indices were applied, indicating the importance to incorporate water-sensitive bands (e.g. Van Niel et al. 2003). On the other hand, hyperspectral remote sensing of rice cropped areas focuses on the retrieval of the optimal number of bands that are best suited to map rice paddies or describe biophysical variables. Thus, the preferred methodology is based on various multiple regression models (Thenkabail, Smith, and De Pauw 2000).

In contrast to low- and medium-resolution optical data, there is no standard method, such as MLC, applicable for the mapping of rice based on radar data. MLC has been found to be unsuitable due to the large variability in SAR data caused, especially, by the differences in planting dates (Le Toan et al. 1997; Chakraborty and Panigrahy 2000). This variation in backscatter results in supervised approaches, with rather high knowledge-based input such as the decision rule-based classifier by Chakraborty and Panigrahy (2000).

5. Outlook and future trends

The future of rice-cropping systems will be based on factors of management and environment influencing the crop growth and yield of rice paddies (Panigrahy et al. 1995). As in most other ecological fields of research, climate change will play a major role in the development of these factors. With about 11% of the total methane flux to the atmosphere, rice paddies significantly contribute to one of the major greenhouse gases (Salas et al. 2007). Future improvement of management practices, i.e. cropping pattern or number of crops per year, could result in a serious increase of these fluxes (Salas et al. 2007).

Furthermore, global warming will increase the frequency of abnormal weather conditions, such as floods, droughts, and storms (Okamoto, Yamakawa, and Kawashima 1998). Since these events usually cause considerable damage to agriculture, remote sensing is needed to quickly assess the extent of damage and the implications for food supply (Okamoto, Yamakawa, and Kawashima 1998). As a further consequence of climate change but also of human development, water resources will become scarcer (Salas et al. 2007). With increasing competition with human water consumption and the predictable increase in water costs, rice paddy irrigation has to improve its water-use efficiency (Salas et al. 2007). At the moment, water usage by agriculture accounts for 86% of the total annual amount in Asia (Salas et al. 2007).

According to Salas et al. (2007), Asian rice production is expected to rise by 70% in the next 30 years, primarily by an increase in yield but also by an expansion of crop area. Thus, urban sprawl will interfere with an extent of rice production area and further hamper the rising demand for food supply. Effective land-use management, for which remote sensing can be a valuable tool, will be crucial. The associated intensification of rice cropping and production based on growing knowledge and technology entails certain risks. A reduction of cropping diversity may cause an increased vulnerability to pests and diseases, resulting in heavy use of agrochemicals (Sakamoto et al. 2009a). This may further lead to an increased contamination of groundwater posing a threat to the health of people. An increase of rice crops per year (up to three crops) or a change in cropping system, e.g. from rainfed to irrigated, could severely affect the watershed ecosystem causing, for instance a changed sediment rate or a depletion of the soils. In order to understand the agro-ecological interplay and to provide a sustainable growth of agricultural activity, monitoring on the basis of remote sensing is necessary (Sakamoto et al. 2009a).

The near future of remote sensing has great potential for the mapping and monitoring of rice cropped areas. The pair of Sentinel-2 satellites, which will be presumably launched in 2014, will have a revisit time of less than 5 days with a spatial resolution of 10 and 20 m, respectively (ESA 2012). Thus, they should be able to overcome the data availability problems for monitoring purposes that other medium-resolution satellites, such as Landsat and SPOT, are facing (Diuk-Wasser et al. 2004). In addition, the EnMAP hyperspectral imager, which is planned for 2015, will promote the research based on spaceborne hyperspectral data. This will most likely bring spaceborne hyperspectral remote sensing closer to operability in rice management. Anyway, independent of the used sensor, remote sensing in rice administration can only be operational if the methods applied are simple to understand as well as easy and inexpensive to incorporate (McVicar 2005).

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