Synergy of Remote Sensing and Modeling for Estimating Ecophysiological Processes in Plant Production

Yoshio Inoue
(National Institute for Agro-Environmental Sciences, Tsukuba, Ibaraki 305-8604, Japan)

Abstract: Information on the ecological and physiological status of crops is essential for growth diagnostics and yield prediction. Within-field or between-field spatial information is required, especially with the recent trend toward precision agriculture, which seeks the efficient use of agrochemicals, water, and energy. The study of carbon and nitrogen cycles as well as environmental management on local and regional scales requires assessment of the spatial variability of biophysical and ecophysiological variables, scaling up of which is also needed for scientific and decision-making purposes. Remote sensing has great potential for these applications because it enables wide-area, non-destructive, and real-time acquisition of information about plant ecophysiological conditions. With recent advances in sensor technology, a variety of electromagnetic signatures, such as hyperspectral reflectance, thermal-infrared temperature, and microwave backscattering coefficients, can be acquired for both plants and ecosystems using ground-based, airborne, and satellite platforms. Their spatial and temporal resolutions have both recently been improved. This article reviews the state of the art in the remote sensing of plant ecophysiological data, with special emphasis on the synergy between remote sensing signatures and biophysical and ecophysiological process models. Several case studies for the optical, thermal, and microwave domains have demonstrated the potential of this synergistic linkage. Remote sensing and process modeling methods complement each other when combined synergistically. Further research on this approach is needed for a wide range of ecophysiological and ecosystem studies, as well as for practical crop management.

Key words: Crop model, Diagnosis, Monitoring, Precision agriculture, Prediction, Remote sensing.

Both remote sensing and process modeling are useful for ecophysiological and ecosystem studies, and for practical crop management. This article reviews recent advances in the remote sensing of plant ecophysiological processes during crop production, with special emphasis on synergistic approaches that combine remote sensing and biophysical and ecophysiological process modeling. First, the research needs for spatial information about ecophysiological variables in agricultural and ecosystem studies are addressed; second, the state of the art in remote sensing technology for crop ecophysiological information is reviewed; and third, synergistic approaches are investigated from a methodological point of view using several case studies for each spectral domain.

1. Remote sensing of ecophysiological processes at field and ecosystem scales

Understanding, predicting, and efficiently managing the ecophysiological processes involved in plant production require a wide range of information, including measurements and diagnostics (Akiyama, 1996). Remote sensing methods have a number of advantages in monitoring actual crop and environmental conditions, since useful information can be remotely acquired on wide-area, non-destructive, and real-time bases. Furthermore, sensor technology allows invisible signals between near-infrared and microwave wavelengths to be detected from a distance.

Remotely sensed data have been used for a variety of applications, such as yield prediction and stress detection. Today one of their major applications is in the area of precision agriculture, which is becoming increasingly important in efficient yet environmentally protective production of crops. Variable rate technology and global positioning system (GPS) devices are key technologies for site-specific crop management (e.g., Robert et al., 1996; Stafford, 1997). For example, site-specific spraying has greatly reduced pesticide use, and irrigation water has been applied efficiently using information on the degree of crop water stress and its spatial variability (Brown and Sieckler, 1995). Hence, remote sensing methods are a powerful tool for providing within- or between-field spatial information (Inoue, 1997; Inoue, 1998; Moran et al., 1997).

Another important application of remotely sensed information is to monitor ecosystems. Since local plant production is closely linked to regional and global environments via carbon and nitrogen cycles as well as air and water pollution, for example, assessing spatial variability and scaling up biophysical and ecophysiological variables are necessary for both scientific and practical purposes (Ehleringer and Field, 1993; Roy et al., 2001).

For instance, net primary productivity (NPP) and net
ecosystem productivity (NEP) must be estimated at local and regional scales in terms of carbon cycle assessment (e.g., Ruimy et al., 1996), where the dynamic changes in the CO₂, H₂O, and energy fluxes are closely related to ecophysiological processes, such as light interception, photosynthesis, and transpiration in the soil-vegetation-atmosphere system. Remotely sensed signatures can provide information that is crucial for wide-area assessment of these variables, since point measurements must be generalized in a spatial context and scaled up to larger areas. The Geographic Information System (GIS) is now used extensively in ecological studies because of the need for archiving and analyzing spatial data (e.g., Cochrane et al., 1999).

2. Overview of the potential and limitations of ecophysiological remote sensing

(1) Recent advances in remote sensing sensors and platforms
Remote sensors for airborne and satellite platforms, which may be useful for estimating plant ecophysiological conditions, are summarized in Table 1. The application of remote sensing to ecophysiological plant monitoring involves at least three important requirements: electromagnetic features, spatial resolution, and temporal resolution (Moran et al., 1997).

1) Electromagnetic Features
Whether useful information can be extracted from plant and soil systems depends largely on physical features, such as spectral wavelength over optical, thermal, and microwave domains, spectral resolution, and polarization. In the solar reflectance domain, hyperspectral signatures should be much more informative than others because of their high spectral resolution (1–10 nm). Hyperspectral imagery can already be obtained using ground-based systems (e.g., Inoue and Penuelas, 2001), airborne scanners such as CASI and AVIRIS (e.g., Teillet et al., 2001), and soon-to-be available spaceborne sensors such as by Hyperion (Perlman et al., 1999). Polarization can also be measured from airborne and spaceborne systems (POLDER; Lacaze et al., 2002), although the spatial resolution of such measurements is coarse. In the thermal domain, a wide range of infrared thermometers and thermography systems are available for ground-based and airborne platforms. Recently, multi-band emission data have become available via space-borne sensors (e.g., ASTER); such data are expected to be effective in the separate estimation of surface temperature and emissivity (Schmugge et al., 2002). Both active and passive sensors are available for measuring the microwave signatures at a range of frequency bands between the Ka (30 GHz frequency; 1.0 cm long) and P (0.3 GHz; 100 cm) bands. Signatures at different polarizations and angles are also available via space-borne sensors such as RADARSAT.

Table 1. Specifications of some current and upcoming spaceborne and airborne sensors for use in ecophysiological applications.

| Sensing system | Spectral region (µm) | Spatial resolution | Revisit cycle | Swath width |
|----------------|----------------------|--------------------|--------------|-------------|
| Landsat-7 ETM+ | 0.45-2.35 (6ch)       | 30 m               | 16 days      | 185 km      |
|                | 10.4-12.5            | 60 m               |              |             |
|                | 0.50-0.90 (pan)      | 15 m               |              |             |
| SPOT-4/5 HRV/IR| 0.50-1.75 (4ch)      | 20 m/10m           | 26 days      | 60 km/2     |
| VEGETATION     | 0.43-1.75 (5ch)      |                    |              |             |
| ERS-1/2 AM-1   | C (5.3 GHz),         | 30 m               | 3 days       | 500 km      |
| C (5.3 GHz)    |                      |                    |              |             |
| RADARSAT SAR   | C (5.3GHz)           | 25 m               | 24 days      | 100 km      |
| EOS-AM1 ASTER | 0.52-0.86 (3ch)      | 15 m               | 5 days       | 60 km       |
| 1.60-2.43 (6ch)| 30 m               |                    |              |             |
| 8.13-11.65 (5ch) | 90 m |                |              |             |
| MODIS         | 0.66-0.87           | 250 m              | 1 day        | 2300 km     |
|              | 0.47-0.53           | 500 m              |              |             |
|              | 0.42-0.87           | 1000 m             |              |             |
|              | 0.91-0.94           | 1000 m             |              |             |
| NOAA-14,15,16 | 0.58-0.68           | 1.1 km             | 12 hr        | 2700 km     |
| AVIRIR        | 0.72-1.1            | 1.1 km             |              |             |
|              | 3.35-12.5 (3ch)     | 1 km/4 km          |              |             |
| IKONOS (SI)   | 0.45-0.90 (pan)     | 1 m                | 11 days      | 11 km       |
|              | 0.45-0.90 (4ch)     | 4 m                |              |             |
| QuickBird (DGI)| 0.45-0.89 (4ch) | 2.8 m              | 1-20 days    | 16 km       |
| (2002)        | 0.45-0.90 (0.7m)    | 0.7 m              |              |             |
| ADEOS-2 GLI   | 0.38-0.83 (4ch)     | 250 m              | 4 days       | 1600 km     |
| (2002)        | 1.05-2.22 (6ch)     |                    |              |             |
|              | 3.72-11.90 (7ch)    |                    |              |             |
| NSCAT         | 13.99 GHz           | 25 m               | 1200 km      |             |
| ENVISAT MERIS | 0.40-1.05 (15ch)    | 300 m              | 3 days       | 1450 km     |
| ASAR          | C (5.3GHz)          | 30 m               |              | 56-120 km   |
| OrbView-3 (OI)| 0.45-0.90 (pan)     | 1-2 m              | 3-16 days    | 8 km        |
| (2003)        | 0.45-0.95 (4ch)     | 4 m                |              |             |
| ALOS AVNIR2   | 0.42-0.89 (4ch)     | 10 m               | 46 days      | 70 km       |
| PRISIM        | 0.52-0.77 (pan)     | 2.5 m              |              | 35 km       |
| PALSAR        | 10 m/20 m           |                    |              |             |
| AIRS          | 1-20 m              |                    |              |             |
| AVIRIS        | 0.41-2.45           | 20 m               |              |             |
| (220ch; 9-4.9 nm) |              |                    |              |             |
| TMS           | 0.38-14.0           | 2.5 mrad           |              |             |
| (10ch; 0.06-1.4) |                    |                    |              |             |
| CASI          | 0.41-0.96           | FOV 15-60°         |              |             |
| (288ch; 2 nm) | 1.61 mrad          |                    |              |             |
| AMS-SAR       | Ku, X, C, L         | 1 - 4 m            |              |             |
| AZM           | 0.42-2.41 (41ch)    | 1.25 - 2.5 m       |              |             |
| 9.2-11.8 (2ch) | 2.5 m              |                    |              |             |
| Ph-SAR        | X, L (polarimetric) | 1.5 - 4 m          |              |             |

2) Spatial resolution
The spatial resolution of data is a major limitation for ecophysiological applications, especially crop management. Since pixel resolution is affected by sensor optics, atmospheric interferences, image registration accuracy, and the detector's signal/noise ratio, the pixel size sometimes has to be much smaller than the scale of the target (Moran et al., 1997). Recently, however, a new generation of satellites has been launched (e.g., IKONOS and...
QuickBird) that provide high-resolution imagery on the order of 1 m on the ground. Another remarkable advance in spatial resolution was made by Landsat–7 in 1999; the pixel size of its images on the ground was half the size of those of previous Landsat sensors in both optical and thermal spectral regions (15 and 60 m, respectively). The SPOT can also provide spectral imagery of similar resolution (10 m).

3) Temporal Resolution

Many potential agricultural applications, such as monitoring crop phenology, growth, and disease, require that data be acquired frequently. Since observation frequency is strongly affected by sky conditions, except for the microwave domain, the revisit cycle must be much shorter than the necessary interval of observation. Although this requirement constitutes a major limitation in satellite remote sensing, commercial satellites such as IKONOS and pointable sensors such as SPOT–HRVIR have recently met this requirement. Sensors with a daily cycle, such as NOAA–AVHRR and SPOT–VEGETATION, are useful for ecophysiological monitoring in agricultural and ecological applications, although their spatial resolution is coarse (on the order of 0.5–1 km) (Roy et al., 2001).

Remote or non-destructive sensing can be applied to ecophysiological measurements using a range of platforms, including ground-based vehicles, such as tractors and radio-controlled helicopters. Besides the use of normal airplanes, the development of various types of airborne platform, such as small radio-controlled blimps (e.g., Inoue et al., 2000a), large stratosphere airships, and some other innovative platforms (Pelton, 1998), has been attempted. Due to their low altitude and stationary features, airships could be ideal for high-resolution, continuous monitoring of plant ecophysiological conditions.

(2) Relation of remotely sensed signatures and crop ecophysiological variables

1) Biomass, leaf area index, and fraction of absorbed photosynthetically active radiation

A number of papers have reported useful relations between remotely sensed spectral signatures and biomass, leaf area index (LAI), vegetation coverage, and the fraction of absorbed photosynthetically active radiation (fAPAR). The most common approach involves an empirical correlation between those variables and vegetation indices that represent a small number of spectral bands. The simple ratio of reflectance at near-infrared and red wavelengths \( \frac{R_{nir}}{R_{red}} \), and the normalized difference vegetation index \( \text{NDVI} = \frac{R_{nir} - R_{red}}{R_{nir} + R_{red}} \) are often used. Furthermore, a variety of vegetation indices have been proposed for more reliable and wider application of such semi-empirical relations (e.g., Huete, 1988; Shibayama and Akiyama, 1989; Govaerts et al., 1999; Haboudane et al., 2002).

The theoretical foundation of vegetation indices has been well examined (e.g., Asrar et al., 1988; Baret and Guyot, 1991; Myneni et al., 1995; Qi, 2001). Since vegetation indices are affected by both plant and measurement conditions, field validation studies for various plant species, locations, and environmental conditions are needed to derive useful, robust semi-empirical relations (e.g., in relation with fAPAR; Daughtry et al., 1983; Steinmetz et al., 1990; Inoue and Iwasaki, 1991; Leblon et al., 1991; Pinter et al., 1993). A comparative study of the relationship between the fAPAR of various plant canopies and six vegetation indices, based on airborne remote sensing data (Inoue et al., 2001), yielded a robust regression between fAPAR and NDVI at regional scales, which agreed well with the theoretical result reported by Myneni and Williams (1994). Despite obvious limitations, spectral indices are simple and useful if they are used within a range of validation.

Since microwave signatures are not affected by weather conditions, SAR (synthetic aperture radar) could be a powerful sensor, especially in monsoon Asia. A number of reports have shown that the microwave backscattering coefficient correlates with biomass and LAI (e.g., Le Toan et al., 1984; Ulaby et al., 1984; Bouman and Hoekman, 1993), although experimental results and the interpretation of microwave backscatter information have not always been consistent, presumably because the microwave backscatter from vegetated surfaces is affected by several factors, including plant biomass, structure, and soil moisture and roughness (Brisco and Brown, 1998). A recent comprehensive study based on season-long daily measurements using a multi-frequency, multi-polarization, and multi-angular sensing system showed consistent relations among the backscattering coefficient, biomass, and LAI for a rice canopy (Inoue et al., 2002). The lower frequency bands, such as C and L, were closely related with LAI and above-ground biomass. The highest correlation coefficient for LAI was found in the cross-polarized C-band at a high incident angle. Biomass was most highly correlated with the L-band, followed by the C-band.

2) Phenology

Most crop management practices are based on phenological stages, such as heading and maturity. Such phenological changes have been related to some spectral signatures, such as seasonal change in NDVI (Boissard et al., 1993), bi-directional reflectance at visible and near-infrared wavelengths (Zipoli and Grifoni, 1994), and spectral shifts in red-edge (Rairyan and Korobov, 1993). Reflected polarization signatures may contain useful information on phenological changes that are accompanied by geometric changes (Ghosh et al., 1993). Microwave backscattering signatures at short wavelengths, such as the Ka-band (GHz), were found to be sensitive to transplanting and heading in a rice canopy (Inoue et al., 2002).
3) Yield

A number of attempts have been made to correlate remotely sensed signatures with the final yield of various crops (e.g., wheat, maize, rice, soybean, barley, sugar beet). The NDVI at critical growth stages such as heading, and the temporal integral of such indices over specific periods, have been correlated to final yield (e.g., Rasmussen, 1992; Yang and Anderson, 1996; Wirnhardt et al., 2001). These are all based on the correlation between above-ground biomass at some stage and final yield. Since senescence during maturity and the duration of the grain filling period are also related to changes in NDVI, the index is correlated with the final yield (e.g., Poutar, 1993; Quarmby et al., 1993). Grain yield at maturity can be estimated by spectral reflectance within the 500- to 700-nm and 900- to 1300-nm wavelength regions (Shibayama and Akiyama, 1991), and at 1100 and 1650 nm (Okawa and Inoue, 1995).

Remotely sensed surface temperature was also related to yield using stress-degree-days (Idso et al., 1980). Since leaf temperature is closely related to water stress, the sum of the canopy-air temperature differences (stress-degree-days) during the grain filling period is correlated with the final yield.

Other data that are useful for yield forecasting can be obtained from microwave backscattering signatures, because the C-band (5 GHz) and L-band (1.5 GHz) are related to biomass, as noted in the previous section. The close relation found between weight of rice heads and backscattering coefficients in the Ka-band (35 GHz) and the Ku-band (16 GHz) may provide useful information about the growth of heads during the grain filling period (Inoue et al., 2002).

In general, these correlations should be used very carefully because the applicability of regression models is strongly affected by the range of the data set, even when the correlations are real correlations based on mechanistic foundations. These regression approaches are usually simple in terms of both model structure and data requirements, but model parameters must be determined for each crop, variety, location, and other variables.

4) Transpiration, photosynthesis, and physiological stress response

Since transpiration is an important part of a plant leaf’s energy budget, remotely sensed leaf or canopy temperatures provide useful information about transpiration and, consequently, stomatal behavior. A number of experimental studies have shown that leaf or canopy temperature has significant relationships with transpiration, stomatal conductance, and photosynthesis (e.g., Jackson et al., 1981). Using infrared thermal imagery, Inoue (1990) clearly demonstrated that canopy temperature responds sensitively to stomatal conductance, transpiration, and photosynthetic rates. The mean surface temperature in the water-stressed canopy was consistently higher than in the non-stressed one, which was closely linked with physiological depression. Remotely sensed infrared temperatures were especially effective for detecting physiological depression and for comparing the physiological status of various canopies on a real-time basis. Any physiological depression caused by water deficiency, disease, insects, or other matters related to stomatal conductance and transpiration can be detected by remotely sensed canopy temperature (e.g., Nilsson, 1991; Yamamoto et al., 1995). Nevertheless, the applicability of canopy temperature alone is limited, because it is also affected by air temperature, solar radiation, vapor pressure deficit, and wind speed. Thus, the first simple approaches for wider applicability involved canopy-air temperature differences, such as stress-degree-days and the crop water stress index (CWSI), which further incorporated the effect of vapor pressure deficit (Jackson et al., 1981). The CWSI was designed to express the degree of water stress as a number between 0 (no stress) and 1 (severe stress). The operational applicability of CWSI has been evidenced by commercial instruments and several application studies using airborne and space-borne thermal imagery (Moran and Jackson, 1991). A simplified approach relating canopy temperature together with a vegetation index to canopy transpiration has been proposed for estimating crop stress conditions (Inoue and Moran, 1997). Other combinations of remotely sensed information and process-based modeling are discussed in detail in the next section.

Vegetation indices have also been related semi-empirically to stomatal conductance and photosynthesis (Sellers, 1987; Verma et al., 1993). Another interesting approach involves the use of hyperspectral signatures to estimate photosynthetic activity directly; one such signature is chlorophyll fluorescence, which can be remotely induced and detected (Cecchi et al., 1994). Chlorophyll fluorescence in the red and near-infrared regions may be a good indicator of the capacity of photosynthetic electron transport, because fluorescence is emitted mainly from photosystem II (PSII). However, no relation between fluorescence, gross photosynthesis, and PAR intensity has been established (Rosema et al., 1998).

Yet another approach is to use the spectral reflectance at a wavelength of approximately 530 nm, which is related to both photosynthetic efficiency (photosynthesis/incident photon flux density) and the relative increase of zeaxanthin in the xanthophylls cycle pool (Filella et al., 1996; Penuelas and Filella, 1998). A high correlation between the normalized reflectance at 531 nm and CO₂ uptake has been found at the canopy scale (Penuelas and Inoue, 2000). Depending on the results of further studies, this relation may be useful for remote and direct estimation of photosynthetic activity.

5) Water, Chlorophyll, and Nitrogen Contents

Since water has a specific absorption spectrum, reflectance spectra may relate to water content or to rela-
to clarify this contribution. Multi-variable statistical methods, such as PCR (principal component regression) and PLSR (partial least squares regression), which are based on empirical determinations, are too complex to be used to determine chlorophyll content. Reflectance at these wavelengths is also used to estimate nitrogen stress, which is highly correlated with the chlorophyll content of green leaves. The sensitivity of reflectance to chlorophyll content is greater at 675 nm than at other wavelengths for low content, and greater at 550 nm for medium-to-high content (Jacquemoud and Baret, 1990). The position of the maximum slope in the increase of reflectance from red to near-infrared was found to shift toward blue with decreasing chlorophyll content (Filella and Aymard, 1995). Inada (1985) showed that the spectral reflectance ratio R800/R550 is the most effective index for estimating the leaf chlorophyll content of rice. Applying R800/R550 to the canopy scale worked only when measurements were taken at an oblique viewing angle under cloudy (diffusive light) conditions (Takebe et al., 1990); canopy nitrogen content correlated poorly with R800/R550 when it was measured at an angle perpendicular to the canopy (Inoue et al., 1998).

The total nitrogen content of a canopy can be estimated using visible and near-infrared wavelengths such as R480, R620, and R840 (Shibayama and Akiyama, 1996), and estimates are improved by also using shortwave infrared wavelengths, such as R1650 and R2200 (Inoue et al., 1998). Based on their simulation study, Daughtry et al. (2000) proposed that the slope of R\text{SWIR}/R\text{red} is useful for estimating leaf chlorophyll concentration at a canopy scale. Yoder and Pettigrew-Crosby (1995) reported that R2132 contributes significantly to estimation of nitrogen in maple seedlings, and suggested that the spectral region between 2000 and 2200 nm is generally useful for this purpose, although exactly how useful it may be remains unclear, especially at the canopy scale. The great contribution of this spectral region is probably because the synthesis and decomposition of enzymes and relative increases in lignin and cellulose are coupled with plant growth, nitrogen supply, and senescence. However, further detailed analyses based on hyperspectral measurements are needed to clarify this contribution. Multi-variable statistical approaches, such as PCR (principal component regression) and PLSR (partial least squares regression), which utilize all hyperspectral data, could also contribute to better estimation of chemical components (Brown, 1993; Cloutis, 1996). Such statistical methods are also useful for estimating canopy mass information because they can be more robust (Takahashi et al., 2000).

3. Synergy of remotely sensed information and process models

As described in Section 2-1, a wide range of electromagnetic sensors can now provide remote-sensing signatures, such as hyperspectral reflectance, thermal-infrared temperature, and microwave backscattering coefficients. Nevertheless, like any other measurement, remotely sensed signatures are never free of noise and error. Furthermore, remote-sensing observations are usually instantaneous and are affected by many factors, such as atmospheric conditions, sun angle, and viewing angle, while the soil-plant-atmosphere system changes dynamically.

On the other hand, ecophysiological modeling is an important approach in both scientific and practical agricultural applications. The integration of various aspects of scientific knowledge is crucial to understanding and predicting plant responses, growth, and yield under real conditions. Detailed and sophisticated simulation models have been developed to describe crop and environmental dynamics for both scientific and practical purposes (Whisler et al., 1986; Penning de Vries et al., 1989, Horie et al., 1995). Despite more than five decades of crop-modeling effort, however, both comprehensive and simple models are of limited effectiveness in the monitoring and prediction of realistic growth and yield (e.g., Landau et al., 1998). Large process models composed of hundreds of algorithms, each containing a set of empirically determined constants, are too complex to be tested, and in some cases have even failed to yield scientific insight (Passioura, 1996). Practically speaking, complicated process models usually require too many input variables or parameters. Collecting all the necessary data for input and determining parameters on the scale of a single field is tedious and sometimes impossible. Hence, especially for operational purposes, simple process models that require fewer input variables are more feasible, provided that they are based on sound and robust principles, and are applied within the range of their calibration data set (Monteith, 1996).

In summary, the advantage of remote sensing is that signatures over broad electromagnetic domains can be detected on remote/non-destructive, wide area basis, or real-time bases, while the issue surrounding is that measurements are usually instantaneous, directional and infrequent, and must be converted to bio-physically meaningful variables. Conversely, the advantage of process modeling is that numerical models can take account of multiple variables, and can provide dynamic simulations as well as predictions under imaginary situations, while the issue is that experimental determination...
of model parameters and model validation are not easy, and that it is tedious or impossible to gather necessary input data. Hence, one of the most promising approaches for effective monitoring and accurate prediction of plant production processes is the synergy of remote sensing and process models, which can reinforce each other.

(1) Methodology of synergizing remotely sensed information and biophysical and ecophysiological process models

A variety of approaches for relating remotely sensed signatures to plant and ecosystem variables are summarized in Figs. 1 and 2. One of the most widely used approaches is the simple regression of target variables on remotely sensed signatures, such as spectral reflectance, thermal temperature, and microwave backscattering coefficients (Fig. 1 ①). Several of these relations are reviewed in Section 2–2.

Nevertheless, physical processes such as spectral reflection, thermal emission, and scattering should be taken into account to extend the applicability and improve the accuracy of relations between remotely sensed signatures and target variables. The first models to be linked with remotely sensed signatures were radiative transfer models, which represent physical processes, such as spectral reflectance/absorption, thermal emission, and microwave scattering. Examples of such models in the optical domain are BRDF (bi-directional reflectance distribution function) models, which can take into account sun angle, sensor angle, and some other spectral parameters (Qi et al., 1995). The reflectance models SAIL and PROSPECT are well-known process models in the optical domain for plant canopy and single leaf analyses, respectively (Verhoef, 1984; Jacquemoud and Baret, 1990). Remotely sensed signatures can be related more systematically to ecophysiological plant variables by inverting these models. For the thermal domain, the energy budget model and mass and energy transfer models are essential for describing thermal emission (Olioso, 1995). The backscattering process of microwaves by a plant canopy can also be described by some scattering models (Attema and Ulaby, 1978; Prevo et al., 1993; Le Toan et al., 1997) that take account of soil, plant, and sensor conditions such as LAI, leaf size, soil moisture, roughness, and incident angle. Plant ecophysiological variables can be estimated by inverting the model, based on the remotely sensed signatures (Fig. 1 ②).

Another type of process model to be linked with remote sensing information is the canopy functioning model, such as the crop growth model and the soil-vegetation-atmospheric transfer (SVAT) model. Canopy functioning models can simulate plant growth or fluxes in vegetated surfaces dynamically using meteorological inputs without remote sensing data (Fig. 1 ③). In addition, these functioning process models can utilize remotely sensed signatures (Fig. 1 ④), or plant parameters estimated by remote sensing (Fig. 1 ⑤), as inputs; they can also be calibrated using remote sensing information to provide more realistic estimates (Fig. 1 ⑥⑦). Further deep linkage between remote sensing and models is presented in Fig. 2. Remote sensing signatures can be simulated by radiative transfer models using output from the functioning models (Fig. 2 ①②③). The remotely sensed measurements are then compared with simulated signatures to fine-tune the functioning models so that they can simulate more realistic signatures (Fig. 2 ④⑤⑦), which, in turn, yield more realistic estimates of ecophysiological variables (Fig. 2 ⑧).

Maas (1988) and Bouman (1992) conducted the first practical studies of this type of synergy. They showed the need for within-season calibration of simulation models, and demonstrated that this calibration effectively reduced model complexity, simplified input requirements, and made the model more operational. This synergistic approach may be a practical and effective method for linking instantaneous remote sensing data with continuous growth simulation, because process models are based on biological foundations and yield robust patterns of growth and development. This approach has an advantage over the direct use of remotely sensed data as inputs and the use of correlations between accumulated remotely sensed indices (e.g., NDVI) and productivity, because the latter two both require frequent remote sensing observations (Wiegand et al., 1986; Christensen and Goudriaan, 1993).

In general, there are two types of synergistic approaches; one approach uses remote sensing data to estimate a few key crop variables (e.g., LAI and evapotranspiration), which are then used to recalibrate the model (Maas, 1993; Moran et al., 1995) (Fig. 1 ② (or ①) and ⑤⑥⑦). This first approach can utilize a wide range of vegetation indices, regression models, and model inversions to estimate crop variables such as LAI and above-ground biomass (e.g., Asrar et al., 1989), which can then be used to recalibrate simulation models.

Another approach is to use the outputs of a crop growth model, such as leaf area index (LAI) and leaf–angle distribution (LAD), to calculate the radiative features (e.g., spectral reflectance and microwave backscatter) of the crop canopy by using a radiation transfer model such as SAIL (Verhoef, 1984). Then, simulated and measured radiative features are compared to recalibrate the crop growth model (Bouman, 1992; Clevers et al., 1994) (Fig. 2 ①②③④⑦⑧). This second approach would be more attractive, provided a crop model is able to output the several geometrical and spectral variables for a canopy that are required by radiation transfer models, and also provided the spectral model is well-calibrated to yield accurate spectral features of the canopy. To simulate canopy reflectance, Moulin et al. (2001) used the output LAI from a growth model for sugar beet (SUCROS) as the input to a
canopy reflectance model (SAIL). The parameters of SUCROS were then optimized to minimize the difference between the simulated and measured reflectances. This approach was useful for predicting sugar beet production at a regional scale. The recalibration approach may be more robust and operational than others, because the process model can provide some normal simulation results based on weather and plant inputs, and because intermittent or infrequent remote-sensing observations can be used efficiently to adjust the model parameters and to re-run the simulations using modified parameters. The tuning of model parameters is usually based on iterative optimization toward the minimized residual difference between observed and simulated data (Olioso et al., 1997; Moulin et al., 1998).

In the following sections, several case studies for each spectral domain will be presented in detail to show the processes and the potential of the above methodological approaches for monitoring and predicting ecophysiological crop conditions.

(2) Case studies in the optical domain

Two case studies of the synergistic use of spectral reflectance signatures and process models are discussed: synergy between hyperspectral reflectance and a biophysical process model for a single leaf, and synergy between canopy reflectance and a growth model for rice canopy.

The first case study is on the synergy of hyperspectral reflectance and a reflectance process model for a leaf (Fig. 2). The hyperspectral reflectance data for leaves of wheat, soybean, peanut, and corn were used (Inoue et al., 1993; Penuelas and Inoue, 1999). The spectral range was 400 to 2500 nm and the resolution was 2 nm for the visible region and 4 nm for the infrared region. Reflectance and the fresh weight of leaves were measured periodically several times during leaf desiccation; after several consecutive measurements, leaves were oven-dried to determine leaf water content and RWC.

When reflectance spectra are available at high spectral resolution, as in this experiment, it may be best to use the whole spectra as input to a hyperspectral radiative transfer model. We utilized the leaf reflectance model of Jacquemoud and Baret (1990). The model has three unknown parameters: leaf water content, chlorophyll content, and a structural index. We performed iterative parameterization of the model using the spectral measurements, making the most of the abundant hyperspectral data from 400 to 2500 nm. The spectrum simulated by the model using the optimized parameters agreed well with the measured spectrum. The directly
Simulation of RS signatures
- spectral reflectance
- brightness temperature
- backscattering coefficient

RS Measurements
- spectral reflectance
- brightness temperature
- backscattering coefficient

Physical process model for RS signature
- Radiative transfer model
- Reflectance model
- Emission model
- Backscattering model, etc.

Real Ecophysiological Variables
- plant [LAI, Biomass, Tr, Ph, Chl, etc.]
- soil [water, C content, etc.]
- flux [H₂O, CO₂, energy, etc.]

Simulation of Ecophysiological Variables
- plant [LAI, Biomass, Tr, Ph, Chl, etc.]
- soil [water, C content, etc.]
- flux [H₂O, CO₂, energy, etc.]

Plant and environmental process models
- Growth model
- SVAT model, etc.

climate data
plant parameters

Fig. 2. Synergy of remote sensing and process modeling (diagram 2). The abbreviations are as in Fig. 1.

measured water content and that obtained by model inversion were highly linearly related. The relations for wheat, corn, and soybean were all very similar and close to 1:1; that for peanut leaf was an exception. This approach has great potential for estimating multiple physicochemical variables, while taking advantage of the data richness of hyperspectral measurements (Inoue et al., 2000b). Nevertheless, in this particular case study, the discrepancy for the peanut leaf, in comparison with the other leaves, suggests that the model does not account appropriately for the structural properties of some species; the structural parameter is expressed as a function of specific leaf area only. Further research is needed to refine the model structure to be more physiologically meaningful.

The second case study is diagrammed in Fig. 1 (1). The model used in this study was a simple process model that simulated the growth and yield of irrigated rice based on weather data (Horie, 1987). Dry matter production was expressed as a function of solar radiation absorbed by the canopy and the radiation use efficiency (RUE; the conversion efficiency of radiation to plant dry mass). The incident solar radiation and fAPAR determined the absorbed radiation. Finally, the grain yield was estimated as a specific proportion (harvest index) of the total dry matter. The model required five initial inputs (date of transplanting, global coordinates of the location, and initial values of dry matter, leaf area index, and developmental index), and two daily input variables (daily values of incident solar radiation and mean air temperature). Due to its simple input requirements, this model was easily applied where common weather data were available (Horie et al., 1995). The model requires parameters specific to rice variety, initial observation data, and calendar-day information such as planting date. The three initial values to be measured on the planting date strongly affected the simulation results; these values are tedious to collect properly for each rice-paddy field. Values of RUE and asymptotic leaf area index were strongly affected by nitrogen availability, air temperature, and other stress factors. The latter two parameters were especially important in estimating biomass productivity. All other parameters were consistent or specific to each variety.

The fAPAR, often used as a key variable in simple process models, was estimated from spectral reflectance data. Spectral reflectance in visible, near-infrared, and shortwave-infrared wavelength regions was measured over differently managed rice canopies for an entire growing season (Inoue et al., 1998). The fAPAR was well correlated with spectral vegetation indices. The use of R1100 and R1650 with R660 and R830 in multiple
regressions significantly improved the prediction accuracy of fAPAR. The use of fAPAR may be unique to remote sensing, because fAPAR is more closely linked with remotely sensed spectral reflectance than other parameters, such as LAI and biomass, and because direct measurement of fAPAR is difficult, especially during the ripening period (Inoue and Iwasaki, 1991).

The performance of the real-time calibration module was tested using remotely sensed fAPAR values. The model was recalibrated with remotely sensed data by optimizing the parameters within the growth model. The optimization process is based on a simplex method: on reaching a certain minimum stable value of residual error, the module determines a set of parameters that are used for subsequent growth simulation. Predictions of the simulation model, with and without remote sensing, showed that even infrequent observations could be used to recalibrate the model. The real-time recalibration module effectively linked the remotely sensed data to a simple crop model. Another useful characteristic of the within-season calibration of a model using remotely sensed data is that recalibration can provide realistic estimates of physiological parameters incorporated into the model without any direct measurements. These physiological parameters may be used for field-to-field comparison of productivity or for variety screening. The timing of tuning and quantity of applied data can also affect the simulation error. The accuracy and stability of estimates and the efficient use of data for calibration are operational issues in these approaches.

(3) Case studies in the thermal domain

As explained in Section 2-2, leaf or canopy temperature can be measured by remote sensing, but the temperature alone cannot necessarily be the absolute estimator of the physiological status of crop plants. This caveat is especially true in the case of non-image measurements, since the leaf temperature is determined by the energy budget of a leaf, which consists of impinging solar radiation, long-wave radiation, and latent and sensible heat transfer. The leaf or canopy temperature is determined as part of the energy budget in the soil-plant-atmosphere system, where energy, water, CO₂, and eco-physiological conditions all fluctuate. Hence, temperature data from infrared imagery provides more quantitatively and reliable information when they are used as inputs into ecophysiological models or stress indices (Fig. 1). Inoue (1987) and Inoue et al. (1990a, 1990b) attempted to estimate leaf transpiration and stomatal resistance remotely, using infrared leaf temperatures. Canopy transpiration has been estimated by a combination of remotely sensed canopy temperatures and an energy- and mass-transfer model under various soil-water conditions (Inoue et al., 1994). In that study, canopy transpiration was expressed as:

\[
\text{Tr} = \frac{(R_n - \rho C_p (t_c - t_a) g_{an})}{\lambda}
\]

(1)

where Tr is the canopy transpiration rate; Rₙ is the net radiation absorbed by the canopy; ρ is the density of air; Cₚ is the heat capacity of air; tₖ and tₐ are the canopy and air temperatures, respectively; g_{an} is the aerodynamic conductance for heat; and λ is the latent heat of vaporization. The value of Rₙ was estimated from Eq. 2 using Rₙ and LAI, which can be estimated by optical remote sensing, and solar elevation (θ), which is calculated as a function of date and time:

\[
R_n = R_n [1 - \exp(-0.5 \text{LAI cosec} \theta)]
\]

(2)

Canopy transpiration values derived from the remote method were validated using those derived using the stem-flow gauge method for soybean canopies (Inoue et al., 1994). The validation in three phases — (1) a daily time course for a particular canopy, (2) ten-minute mean values for various canopies, and (3) daily total values for canopies under various soil and meteorological conditions — showed excellent agreement. It was concluded that the remote method, based on measurements of canopy surface temperature, could yield reasonable estimates of canopy transpiration and conductance over a wide range of soil-water and micrometeorological conditions. This model constitutes the main part of the SVAT model. The SVAT model consists of major physical relations among the flow of water, energy, and CO₂, as well as a wide range of biophysical soil, plant, and atmospheric parameters, which can be further linked to a regional climate model (Olioso, 1995). Further synergistic use of remotely sensed temperatures and the SVAT model has proved useful for dynamic estimation of transpiration, photosynthesis, and soil–water content (Olioso et al., 2001).

(4) Case studies in the microwave domain

Since microwave backscattering signatures are affected by plant parameters (LAI, water content, canopy height, biomass, and geometry), soil parameters (water content, surface roughness), and measurement configurations (frequency, polarization, angle), process modeling has shown promise with respect to understanding and predicting the multivariable interactions between microwave backscatter and plant and soil variables. The backscattering coefficient (\(σ^2\)) for the whole canopy has been expressed using a simple process-based model (the water cloud model; Attema and Ulaby, 1978), which has proved useful for a range of crop types and conditions (e.g., Prevot et al., 1993; Moran et al., 1998; Champion et al., 2000):

\[
σ^2 = κ_{veg}^2 + τ^2 \sigma_{soli}^2
\]

(3)

\[
σ_{veg}^2 = AV_1 \cos \theta (1 - τ^2)
\]

(4)

\[
τ^2 = \exp[-2 BV_2 / \cos \theta]
\]

(5)

where \(σ_{veg}^2\) and \(σ_{soli}^2\) are the backscattering coefficients in power units (m² m⁻²) for vegetation and soil, respectively; \(τ^2\) is the two-way attenuation through the canopy; \(θ\) is the incident angle; \(V_1\) and \(V_2\) are the descriptors of the canopy; and A and B are coefficients that depend on canopy type. The variable \(σ_{soli}^2\) is usually expressed as a function of soil moisture. Prevot
et al. (1993) and Moran et al. (1998) showed that this model could be used to estimate LAI in wheat and cotton canopies, respectively. The latter study also showed that the use of dual-frequency bands (Ka and X) could simultaneously estimate LAI and soil moisture beneath the canopy. A recent experimental study for a rice canopy provided more definitive results on the interaction between backscattering signature and vegetation only, since the background in paddies is always the surface of a water body (Inoue et al., 2002). That is, for paddy rice, we can simply assume that the scattering from the canopy background is constant \((\sigma_0^m)\). A comprehensive data set for a rice canopy was used, including all microwave backscattering coefficients for all combinations of five frequencies (Ka: 35.25 GHz, Ku: 15.95 GHz, X: 9.6 GHz, C: 5.75 GHz, and L: 1.26 GHz), all combinations of vertical (V) and horizontal (H) polarizations (HH, VH, HV, and VV), and four incident angles \((25^\circ, 35^\circ, 45^\circ, \text{and} 55^\circ)\) for the entire rice crop season (from before transplantation to after-harvest cultivation). Since both canopy descriptors can be represented by LAI or total fresh weight (TFW), such that \(V_1 = V_2 = V = \text{LAI}\) or \(V_1 = V_2 = V = \text{TFW}\), the backscatter for a rice paddy can be expressed (in dB) as follows:

\[
\sigma^d = 10 \log \left( A V \cos \theta \left( 1 - \exp \left[ \frac{-2B V}{\cos \theta} \right] \right) \right) + \exp \left[ \frac{-2B V}{\cos \theta} \right] \sigma_0^b. \tag{6}
\]

In Eq. 6 there are three parameters, \(A, B,\) and \(\sigma_0^b\), to be determined by iterative optimization (Fig. 2). The degree of fit can be estimated using the correlation coefficient \(r^2\) between the estimated and measured values of \(\sigma^d\) after parameterization. The values of \(r^2\) for all combinations of frequency, polarization, and incident angle were compared in two cases; one utilizing LAI and the other utilizing total biomass as the vegetation descriptor. For LAI, the fitting level was highest in the C-band followed by the L-band, whereas the Ka-, Ku-, and X-bands were poorly correlated. The high correlations \(r^2 = 0.95-0.99\) found for HH-polarization and cross-polarization in the C-band suggest that the simple scattering model is highly applicable to the C-band when LAI is used as the canopy descriptor. For total fresh weight (TFW), the fit was high in both the L-band and C-band, but higher in the L-band. This result implies that TFW and LAI are better estimated by the L-band and C-band, respectively. In contrast, the fit was poor for the Ka-, Ku-, and X-bands, which suggests that the simple model may not be suitable for representing the interaction between microwaves in the Ka- and Ku-bands and a rice canopy when LAI or TFW is used as the canopy descriptor. The penetration depth of microwave into the canopy should be much smaller for higher frequency bands than for lower ones, especially in dense or thick canopies. Therefore, high frequency bands (Ka and Ku) may provide little information about the whole canopy, such as the LAI and total biomass.

4. Conclusion

Despite the discussion of crop-model limitations (Passioura, 1996), numerically modeling ecophysiological processes can help integrate scientific information to predict crop growth, yield, and quality of products under various environmental and management conditions. Simulation of ecophysiological processes under imaginary conditions, such as doubled CO₂ concentration, is possible only using such models. Nevertheless, the models need to be validated over a wide range of environmental and management conditions. Furthermore, in situ information is crucial if models, even well designed process models, are to be applied over larger scales, since they require input data and parameters for each canopy or field on local or regional scales.

On the other hand, as reviewed in Section 2-1, due to the advances in both sensor and computer technologies a wide range of physical signatures can be remotely acquired at leaf, canopy, and ecosystem scales. However, any measurement involving remote sensing data can provide limited information about the soil-plant-atmospheric system in the field. Thus, the synergy of the remote sensing method and process models should be promising in both ecophysiological and regional studies, as well as operational crop management.

As presented in several case studies, remote sensing information can be directly assimilated into biophysical or ecophysiological process models. Another useful approach involves the numeric parameterization, i.e., tuning of process models. Several numeric iteration methods are available for optimizing parameters or initial conditions. As in modeling approaches, validation and sensitivity analysis are important processes in the synergistic linkage of process models and remote sensing signatures. Technical assessment of accuracy, error propagation, and parameter sensitivity should be considered in each scientific or practical application. Further research on biophysical remote sensing is needed for accurate monitoring and prediction of ecophysiological processes in plant production.

This article reviewed the state of the art in agricultural remote sensing from the viewpoint of ecophysiological studies and crop management, where the main focus was on the synergy of remote sensing and process models. Thus, all aspects of agricultural remote sensing might not have been thoroughly reviewed, but I hope it provides useful information and insight for ecophysicists, crop modelers, and field managers.

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