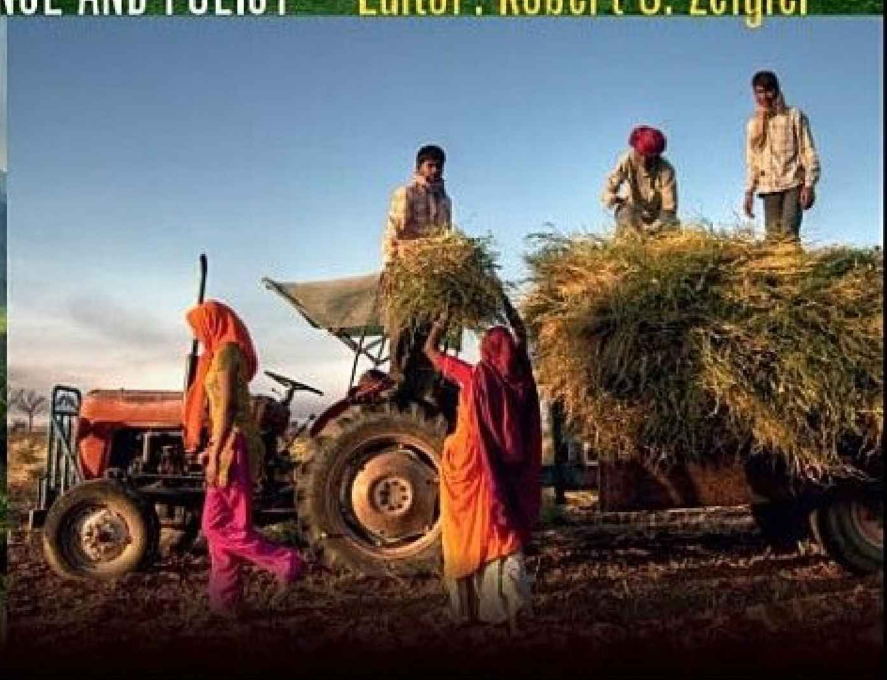



SUSTAINING GLOBAL FOOD SECURITY

THE NEXUS OF SCIENCE AND POLICY

Editor: Robert S. Zeigler

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For Willow, Pearl, Sylvie and Jack: The next generation

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Remote sensing for sustainable agricultural management

Andy Nelson

Introduction

Remote sensing is the means to obtain information about an object or phenomenon without any physical contact with that object (Lillesand *et al.* 2015). The first remote observations using photographs were from hot air balloons in the mid and late 19th century; however, it wasn't until the start of the 20th century that aerial photography was used more systematically and more scientifically for surveying, topographic mapping and characterising the Earth's surface, with much of that development being driven by military purposes (Campbell and Wynne 2011). Satellite-based remote sensing started in the 1970s and since then its use for Earth observation purposes has increased dramatically. More recently, large constellations of small satellites and airborne platforms, such as unmanned aerial vehicles (UAVs) or drones have become viable and cost-effective methods to acquire remote sensing information.

It is the ability of remote sensing to provide non-destructive, automated and regular observations for any location on the planet that has led to its increasing application in many sectors. The field has expanded rapidly in recent years, in both technology and applications, and this chapter can only touch upon a few aspects of its use for agriculture (e.g. it does not cover ground-based remote sensing nor the developments in downstream processing of remote sensing images).

This introduction briefly describes the main characteristics of remote sensing for acquiring spatial and temporal information about the physical, chemical, biological and geometrical aspects of agriculture. This is followed by some examples of remote sensing for assessing sustainable agricultural management options (i.e. at local and regional levels) and potential entry points for remote sensing information to measure progress towards sustainable agricultural management (at national and international levels). The chapter ends with some of the factors that will shape the future use of remote sensing in sustainable food systems.

More detailed information can be found in the following excellent resources: remote sensing platforms and sensors in general (Toth and Jóźków 2016); remote sensing applications in agriculture (Pinter *et al.* 2003; Atzberger 2013; Mulla 2013); and, the role of sensors, information technology and big data in agriculture (Kamilaris *et al.* 2017; Wolfert *et al.* 2017).

Remote sensing instruments, or sensors, detect and measure the electromagnetic radiation that is reflected or emitted from an object. These sensors can be described based on their source of radiation, their resolution, the wavelengths they use and the platforms they are housed in.

Passive and active sensors

Sensors can be either passive or active, which refers to the source of radiation they use. Passive sensors (radiometers and spectroradiometers) measure radiation that is emitted or reflected by an object and transmitted through the Earth's atmosphere to the sensor. The radiation comes from the sun and hence they are dependent on sunlight and relatively cloud-free conditions to acquire information. Active sensors (LiDAR[1] and synthetic aperture radar[2] or SAR) emit their own radiation, which is transmitted to the Earth's surface and then reflected or backscattered by that object back to the sensor (Lillesand *et al.* 2015). Both LiDAR and SAR can operate independently of sunlight, but LiDAR, which is usually based on near-infrared wavelengths for terrestrial mapping applications, is affected by snow, rain and dust in the atmosphere, whereas SAR is affected by intense rain or dense clouds only in the shorter microwave wavelengths. LiDAR is used to generate detailed and accurate three-dimensional models of the Earth's surface and objects upon it. SAR has particular value for observations during the monsoon period in the tropics and during winter in temperate zones when cloud cover is pervasive.

What is meant by resolution in remote sensing?

The spatial (or geometric) resolution of a sensor refers to its ability to resolve or separate one object from another. For most remote sensing platforms, this can range from centimetres (i.e. UAVs) to kilometres (i.e. weather satellites) per image pixel. Spatial resolution is related to the characteristics of the sensor and the altitude of the platform it is on. Higher spatial resolution images have more spatial detail, with the highest resolutions able to identify individual plants or plant organs, but typically a high spatial resolution image will cover a much smaller area of the Earth's surface than a low spatial resolution image.

The temporal resolution of a sensor refers to the frequency with which an object can be observed. This can range from a single observation to many repeat observations over time. Terms such as multi-temporal and hyper-temporal remote sensing relate to the frequency of the observations in relation to the rate of change of the physical and chemical properties of the object being observed. Repeated observations of agricultural land through the season provide excellent monitoring capabilities to assess changes in soil and water conditions or the phenology and status of the crop (Boschetti *et al.* 2017) (Plate 19.1). The revisit time of sun-synchronous satellites (usually in a low orbit between 180 and 2000 km) dictates their temporal resolution, whereas geostationary satellites can image the same area almost constantly, but with much lower spatial resolution because of their much higher altitude, over 35 000 km.

The sensitivity of the sensor to the magnitude of radiation that it receives is called the radiometric resolution. A low radiometric resolution sensor can only provide imagery with eight or 16 different pixel values (eight or 16 shades of grey is a good analogy), whereas a higher radiometric resolution sensor could provide imagery with 256 or 65 356 different pixel values. The higher the radiometric resolution, the more sensitive the sensor to small changes in reflected or emitted radiation. This is particularly important for characterising the spatial variation of a surface, sometimes referred to as texture analysis.

A sensor can detect radiation in more than one wavelength and many passive sensors have several bands or channels where each band refers to a range of wavelengths. The number of bands is referred to as the spectral resolution of the sensor. Multispectral sensors, such as Landsat-8 or Sentinel-2, typically have between four and 12 relatively wide bands, whereas hyperspectral sensors can have up to hundreds of narrower bands. The higher the spectral resolution, the more opportunity to identify and separate different physical and chemical properties of vegetation, soil and water.

These four resolutions are related to the information requirements of the remote sensing application. Mapping crop type may require multispectral images several times per season with pixel sizes that are smaller than the field sizes. Mapping field sizes may require very high spatial resolution. Mapping crop varieties may require hyperspectral images once or twice a season. Detecting pests or diseases may require spatially detailed hyperspectral imagery. Each sensor has its own combination of spatial, temporal, spectral and radiometric resolutions (see Toth and Jóźków (2016) for a list of current, major remote sensing systems). There is a trade-off here because there is no single sensor with high resolutions across the board, although improvements in sensor technology are reducing this trade-off and a combination of sensors, so-called cooperative sensing (Toth and Jóźków 2016), may remove it completely.

Remote sensing wavelengths and their use in agriculture

The most frequently used portions of the electromagnetic spectrum for Earth observation are in the visible (400–700 nm), near, mid and thermal infrared (700 nm to 1 mm) and microwave (>1 cm) ranges of wavelengths (Campbell and Wynne 2011). Shorter, ultraviolet wavelengths (100–400 nm) also have some application for mineral and atmospheric properties but are not discussed here.

The visible portion of the spectrum, from violet to red, is relatively small and is the part associated with light and colour. It is also the range that photosynthetic organisms are able to use for photosynthesis. Chlorophyll in plants absorbs light in the red and blue wavelengths light but reflects enough in the green wavelengths to give plants their characteristic green colour (Lillesand *et al.* 2015). Visible passive remote sensing bands are usually labelled blue, green, yellow (not common) and red, with red and green bands being of most interest for soil and vegetation applications.

The infrared (IR) portion of the spectrum is particularly useful for monitoring vegetation, especially in the near-infrared (NIR) and mid-infrared (sometimes called shortwave infrared or SWIR) range. Healthy plants with high water content and dense foliage strongly reflect NIR. The difference between absorption in red and reflection in NIR is the basis for vegetation indices such as the normalised difference vegetation index (NDVI) to quantify plant density and status (Rouse *et al.* 1974; Tucker 1979). Sparse vegetation reflects more red and less NIR than dense vegetation and a stressed plant will absorb more NIR than a healthy one.

There are many possible spectral indices for vegetation, water and soil, based on different band combinations in the visible, NIR and SWIR wavelengths that relate to the relative absorption and reflection of surfaces (see Hatfield *et al.* (2008) for a relevant list of indices for agriculture). Detecting temporal and/or spatial differences in these indices is the basis for many remote sensing applications to map and monitor crop or canopy characteristics (Gitelson *et al.* 2005; Viña *et al.* 2011), soil physical structure (Anderson and Croft 2009), moisture or water content or the presence and intensity of abiotic and biotic stresses (Hatfield *et al.* 2008).

Active LiDAR operates in different parts of the spectrum depending on the application. Here we focus on LiDAR systems that use NIR wavelengths for terrestrial mapping. LiDAR systems measure the time required for a laser pulse to travel from the sensor to the object and back. That time and the speed of light are used to calculate the distance between the sensor and the object accurately. LiDAR systems can rapidly scan a given area and record thousands of data points (point clouds) that can be used to generate 3D models of the object. LiDAR scanning has applications for phenotyping (Lin 2015), crop canopy height estimation (Eitel *et al.* 2016) and the measurement of field slopes and soil erosion.

Remote sensing in the longer, thermal infrared (TIR) wavelengths measures the emitted energy of an object (its radiant temperature) rather than its reflected energy. TIR wavelengths have not been used for agriculture as much as the visible, NIR and SWIR wavelengths, but the ability to measure the surface temperature of soil and vegetation has applications for early detection of crop stresses, pests and diseases and water stress. Changes in the thermal properties of these surfaces can also guide the scheduling of farm activities such as irrigation and harvesting (Khanal *et al.* 2017).

Finally, SAR sensors operate in the microwave portion of the spectrum. SAR works by transmitting microwave pulses towards an object and detecting how much of the microwave energy is reflected or backscattered back to the sensor. SAR images most commonly display the intensity of the backscattered signal. For example: very high backscatter is associated with man-made surfaces in urban areas, high backscatter with dense vegetation, moderate backscatter with crops and low backscatter with water. However, the intensity of the reflected signal depends on the object's moisture content, relative permittivity, surface roughness, slope and orientation relative to the direction of the microwave pulse. It also depends upon the wavelength, polarisation and incidence angle of the SAR sensor (Moreira *et al.* 2013), which must all be taken into consideration in the processing and interpretation of the SAR signal.

SAR had often been seen as complementary to optical remote sensing for agriculture applications but the availability of several new space-borne SAR platforms using short (X-band), medium (C-band) and long (L-band) wavelengths means that SAR based applications are increasing for the estimation and mapping of crop biomass, height, leaf area index (LAI), crop water content, crop phenological stage, soil tillage, residue mapping and soil moisture (McNairn and Brisco 2004; Lopez-Sanchez and David Ballester-Berman 2009).

New platforms and their implications for agriculture

Satellite remote sensing has been the main source of imagery for agricultural applications since the 1970s when Landsat 1 was launched. The high cost of the satellite and ground segments required for Earth observation meant that national and international space agencies (e.g. NASA, ESA, JAXA) dominated the early investments. These agencies still have a large presence and their free-of-charge imagery from Landsat, MODIS and Sentinel provide, regular (daily, weekly, monthly) multispectral and SAR data at spatial resolutions (from 10 to 500 m) that form the basis of many agricultural applications.

Not all space agency satellite imagery is free of charge and there are various business models whereby the products from agency platforms are commercialised. For example, SAR data from the COSMO SkyMed satellites of the Italian Space Agency Space is sold by eGEOS and MDA is the commercial provider for data from the Canadian Space Agency's RADARSAT-2 SAR platform. Large corporations or companies (e.g. Airbus, MDA) also have a stake in Earth observation with specialised or tailored platforms such as SPOT 6/7, WorldView or RapidEye that provide higher spatial resolution multispectral imagery (less than 1 or 2 m) from a constellation of satellites as well as a range of 'map ready' products and services at a cost.

In recent decades, the number of national space agencies operating satellite platforms has rapidly increased and some agencies have expanded their number of platforms (Belward and Skøien 2015). For example, the Copernicus program, which is directed by the European Commission in partnership with ESA, is the world's largest single Earth observation program. At the same time, the number of commercially operated platforms has increased due to reduced costs for satellite development, deployment and operation, as well as the increase in market opportunities for the use of Earth observation data.

The development of small, relatively low-cost platforms, has been the latest revolution in satellite remote sensing. The miniaturisation of components and the use of off-the-shelf components has significantly lowered costs, enabling companies such as Planet to launch dozens of small platforms at a time to form large constellations that provide, or will provide, multispectral imagery with high spatial and temporal resolution and even video capability (e.g. Iris from Urthecast 2017). This new stream of information can remedy some bottlenecks in agricultural applications of remote sensing where fields have been too small to see individually, or where observations were not frequent enough or not spatially detailed enough to capture the known variability in land and crop characteristics. Although these higher spatial resolution (less than 10 m) sources of data are distributed on a commercial basis, some of them are freely viewable through web-based mapping or visualisation tools such as Google Earth/Maps and Bing Maps and are often used for map validation or citizen science applications (Belward and Skøien 2015).

The second biggest change has been in the development of civilian UAV platforms, compact sensors and user-friendly software for flight planning and imagery processing. UAV platforms can carry simple optical cameras, multispectral, hyperspectral and thermal sensors, and UAV based LiDAR is an emerging technology and there has even been progress in the miniaturisation of components for SAR. The very high resolution of UAV images has a wide range of applications for precision agriculture, as well as for supporting more rapid analysis of data in experimental stations (Zhang and Kovacs 2012; Mulla 2013; Houborg and McCabe 2016; Tokekar *et al.* 2016).

Since the first launch by the USA in 1972, at least another 33 nations have financed missions through government or commercial programs, meaning that more people in more countries have access to Earth observation data than ever before (Belward and Skøien 2015). The current quantity, quality and diversity of Earth observation data, which provides a unique view of land resources, is unprecedented. As a consequence, the range of research, prototype and operational applications for agriculture is increasing, as is the innovation in how remote sensing data can be exploited. The next section provides only a few examples in the context of sustainable agricultural management.

Remote sensing information to assess sustainable agricultural management options

Although some areas, especially in sub-Saharan Africa still have opportunity for agricultural land expansion – which in itself poses challenges for environmental management (Green 2005) – most regions require higher and more sustainable production per unit land to achieve the 70% increase in production that is predicted to be needed by 2050 (Godfray *et al.* 2010; Foley *et al.* 2011). Some environments that contain important food production systems are approaching critical ecological thresholds that will limit their ability to provide the ecosystem services necessary to sustain these systems and the rural livelihoods that depend upon them (Campbell *et al.* 2017). The limited or stagnating productivity growth in these systems comes from a confluence of environmental, social and economic constraints such as degradation or contamination of the soil, sub-optimal management, insecure land tenure, insufficient economic or physical access to inputs, lack of incentives or opportunities to invest, a loss of biodiversity, the spread of pests and diseases, and increased exposure to water and temperature stresses from climate change. In some cases, this stagnation has become a collapse, which has led to conflict, migration and land abandonment (FAO 2017a). These lagging areas are hotspots of rural poverty and land degradation: those who can leave do so, on a seasonal or permanent basis, to find employment in already over-burdened cities. This results in an increasing gap between food systems that have benefitted from investment, and have thus contributed to the global progress in food security, and those that have been left behind.

Transforming rural food systems to meet the growing and diversifying urban demand is essential for increasing sustainable production. Investing in rural–urban linkages would provide rural areas with greater access to technology, services and more diverse markets. In turn, this would increase the diversity and value of food products, generate more rural employment opportunities in farm and non-farm sectors, reduce post-harvest food losses and waste, and reduce rural poverty and migration. Different transformations will be needed in different places and the benefits will vary too.

From a biophysical and land management perspective, these transformations will likely include a range of sustainable, resource-efficient and climate-smart practices, such as agroecology, agro-forestry, integrated crop–livestock–fish systems, precision agriculture and conservation agriculture to ensure that production increases also protect and enhance the natural resource base (FAO 2017a). These transformations will require spatial information to identify what type of practice should be considered for particular environmental and socio-economic conditions as part of a critically assessment of the potential benefits and trade-offs (Giller *et al.* 2009). Some example contributions of remote sensing and other spatial data to better understand the current and potential status of agricultural management practices are considered next.

Future crop suitability

Sustainable and climate-smart crop production requires knowledge on which climate variables affect crop production in order to assess the impact of climate change on the extent and range of suitable production areas. Spatial information on crop extent and calendar can be combined with climate change scenario data in ecological niche models to estimate the future geographic distribution of crops (Plate 19.2), their likely exposure to pests and diseases and the required abiotic traits for successful crop adaptation (Jarvis *et al.* 2012).

These assessments need to document the sources of uncertainty in their predictions and ensure that the climatic variables used reflect the change in exposure to extremes that can pose severe limitation on future productivity, such as changes in the number of days during flowering where the temperature is over 35°C and humidity is greater than 90%.

Crop intensity suitability

The potential for sustainable intensification can also be assessed with remote sensing and other spatial data. Gumma *et al.* (2016) used multi-temporal MODIS imagery to map the spatial and temporal patterns of rice-fallow systems in South Asia and identify suitable areas for growing short-duration grain legumes on residual moisture after the rice crop. Krupnik *et al.* (2017) used multi-temporal Landsat imagery to assess the amount of fallow and rain-fed cropland in south-west Bangladesh that could be used for intensified dry season cereal production using surface water irrigation (Plate 19.3).

Generating plausible remote-sensing-based estimates of the areas that are environmentally suitable for increased intensity can form part of larger assessments to determine if there additional interventions are needed to ensure a sufficient level of access to the technology, resources and markets needed to enable the additional crops to be established, managed and sold.

Crop yield variability

Remote sensing has been used to estimate yield since the 1970s (MacDonald and Hall 1980) and there are two main groups of approaches. The first relates vegetation indices or signal intensity to yield, either through empirical regression models or by relating them first to biomass and then yield via the harvest index (Atzberger 2013; Rembold *et al.* 2013; Jin *et al.* 2017). Although relatively easy to implement at scale, these empirical relationships are often location and season specific and require field measurements to apply them in new settings. The second approach assimilates remote-sensing-based estimates of plant development, such LAI into crop growth simulation models (CGSM) that describe the physiological mechanisms of crop development and estimate yield (Rembold *et al.* 2013). This is a more complex and computationally expensive process and most CGSMs require a large number of parameters that cannot be easily estimated for every location to be mapped.

New approaches that combine CGSMs, statistical models and remote sensing information within cloud computing platforms show promise for more scalable yield estimation and yield variability mapping at very high spatial resolution (Lobell *et al.* 2015; Burke and Lobell 2017). These detailed representations of the spatial and temporal variability of crop yield (Plate 19.4) can contribute to better understanding of existing practices and targeting of improved practices.

Monitoring soil-conserving technology

Improved tillage practice and improved crop residue management can reduce soil erosion and increases soil organic matter, water infiltration and nutrient cycling, as well as reducing costs for establishment and production. Spectral reflectance signatures for soil and crop residue can be derived from multispectral and hyperspectral remote sensing sources and have been used to detect and map different tillage practices (South *et al.* 2004; Bannari *et al.* 2006; Daughtry *et al.* 2006).

Larger scale implementations can take advantage of the increase in optical and radar remote sensing data to cover larger areas more frequently, but they will require systematic ancillary data collection to account for the spatial variation in soil, terrain and vegetation cover, as well as the temporal variation in soil preparation and planting (Zheng *et al.* 2014). Thermal remote sensing may also have a role to play in monitoring soil-conservation technology, because fields with higher levels of crop residue can be expected to have a lower surface temperature (Khanal *et al.* 2017).

Assessing and monitoring water-conserving technology

Alternate-wetting-and-drying (AWD) in rice is one example of a water-conserving technology that can reduce water use by up to 30%, compared with the continuously flood conditions in many rice systems, without impacting yield (Lampayan *et al.* 2015). It is also one of the most promising mitigation options for reducing agricultural methane emissions (Sander *et al.* 2014). Remote sensing information on rice crop area, rice crop calendars in combination with rainfall, soil properties and water management information can provide a climate-based suitability assessment (Plate 19.5) of the upper bounds of the water-saving potential of AWD, as part of a more comprehensive evaluation (Nelson *et al.* 2015; Sander *et al.* 2017). Monitoring of the actual area where AWD is practised may be possible with multi-temporal remote sensing using long wavelength (i.e. L-band) SAR imagery, which can penetrate the rice crop canopy to some extent and provide information on dry and inundated periods, but this requires more research to assess its viability and accuracy. This has applications beyond water conservation because AWD may allow rice farmers to qualify for carbon credits, which would require verifiable data that support the claim that a farmer used AWD for a given area for a given time period.

Monitoring the performance of other water-conserving technologies such as drip irrigation systems can be achieved with UAV and other high spatial resolution platforms based on thermal and multispectral information incorporated into water-balance models (Santos *et al.* 2008) or energy-balance models (Ortega-Farías *et al.* 2016). Thermal bands are of particular interest because plant stress is more rapidly visible in the longer wavelengths in thermal images than in the visible and near infrared wavelengths of multispectral images.

Although these examples refer to specific implementations, all of them can take advantage of the continuous developments in remote sensing technology (improvements in spatial, temporal, spectral and radiometric resolution; increasing number of space, air and land based platform options) to provide more accurate, timely and detailed assessments of agronomic management practices.

Remote sensing information as part of a framework to measure progress towards sustainable agricultural management

The previous section listed a small number of local, national and continental examples of the use of remote sensing information to assess agricultural management options and the extent to which agricultural practices are adopted. Once adopted, the extent of adoption or the environmental impact of their adoption needs to be monitored to track progress towards sustainable development targets. One of remote sensing's greatest advantages is its worldwide coverage and frequent revisit time, which makes it a valuable source of environmental monitoring information. It is at the global institutional level where there is opportunity for remote sensing to be accepted as part of a larger framework for monitoring progress towards sustainable food production systems. When it is included as part of a global monitoring framework it can be more easily adopted at national level as well, though one does not preclude the other.

In this section, the potential role of remote sensing for sustainable agricultural management within the monitoring framework for the sustainable development goals (SDGs) is discussed, before concluding the chapter with comments on the enabling environment for this to happen. The section will focus on only one indicator within one target of one goal, as an example of potential for Earth observation to support the 2013 Agenda for Sustainable Development. The same exercise could be repeated for any of the goals and a broader assessment of the potential of remote sensing information has already been made by the Group on Earth Observations (GEO 2017).

The challenge of sustainably meeting future global food needs is most clearly associated with the 2nd SDG:

> *Goal 2 – End hunger, achieve food security and improved nutrition, and promote sustainable agriculture (UN 2017).*

Meeting this goal requires better use of limited, and often degraded, natural resources, and better incorporation of our understanding of plant–environment interactions into sustainable food production policies and their implementation targets. This is most clearly associated with Target 2.4:

Target 2.4 – By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality (UN 2017).

Each target requires indicators to benchmark and track progress towards them. All SDG indicators are now part of an agreed global indicator framework, developed by the Inter-Agency and Expert Group on SDG Indicators. Target 2.4 has one indicator:

Indicator 2.4.1: Proportion of agricultural area under productive and sustainable agriculture (UN 2017).

This indicator is currently classed as a Tier III indicator, meaning that there is no internationally established methodology or standard available to measure and monitor it. There is ongoing work to agree on the definition of sustainable agriculture and its components, which is essential before this indicator can be more clearly defined, pilot tested, validated, endorsed and implemented.

Whatever agreements are made, the most likely mode of data collection will be via agricultural surveys to collect information on sub-indicators on the social, economic and environmental dimensions of sustainability. The implementation of these surveys often falls under the remit of national statistical agencies, but there have been questions over the ability of agencies in many countries to deliver the timely, reliable and high-quality data (Jerven 2013). The SDGs will require the collection of more data than these surveys currently collect. The implied higher cost of this data collection would be a double penalty if the quality of social, economic and environmental data continues to be insufficient for decision and policy making (Jerven 2014).

This massive data collection effort (UN 2014), especially in the environmental dimension, can be complemented by observations from remote sensing or estimates from other sources of spatial data (FAO 2017b) to assess changes in the stock of the natural resources due to the adoption of improved management practices. Complementarity is the key word here. Investing in remote sensing and other emerging sources of low-cost, large-scale data (such as from social media, sensor networks or mobile phone networks) should not replace investments in national surveys and capacity development in statistical bureaus. A more suitable approach would be to identify where remote sensing can: (1) improve sampling strategies through better understanding of the spatial and temporal variability in environmental conditions; (2) validate existing estimates by providing detailed, independent measurements; or (3) provide new information that could not be captured cost effectively any other way.

Table 19.1 lists the various themes and sub-indicators within the environmental dimension and lists current and potential sources of remote sensing information or other spatial data that could contribute to them. Links to other SDG indicators are provided to highlight additional areas where the same remote sensing information could contribute to other SDG data needs.

Table 19.1. Potential contributions of remote sensing and spatial data for environmental sub-indicators under SDG Indicator 2.4.1.

Sub-indicators and links to other SDG indicators from FAO (2017b).

Proposed theme	Proposed sub-indicators	Current and potential sources of remote sensing and other spatial data	Possible links with or contributions to other SDG indicators
Quality and quantity of soil resources	Topsoil organic carbon content and soil loss due to water erosion	• Gridded soil information from GSOCmap (Global Soil Partnership and FAO 2017a), SoilGrids and AfSIS (Hengl *et al*. 2014, 2017) • Soil spectral libraries (Viscarra Rossel *et al*. 2016) • Multispectral sources such as Landsat (Vågen *et al*. 2013) and Sentinel-2 • Soil organic carbon content from hyperspectral remote sensing platforms such as EnMAP (Guanter *et al*. 2015) • Inclusion of remote sensing data in soil water erosion models (Vrieling 2006)	15.3.1 Proportion of land that is degraded over total land area
Water use	Water extraction for agriculture from surface and groundwater as a percentage of available water	• Spatial and temporal estimates of surface water availability based on the spectral properties of water from Landsat, Sentinel-2 and other multispectral platforms (Pekel *et al*. 2016), synthetic aperture radar (SAR) imagery and altimetry (Wdowinski *et al*. 2008; Villadsen *et al*. 2016), LiDAR sources or combinations (Lamarche *et al*. 2017) • Microwave remote sensing of soil moisture from platforms such as the Soil Moisture and Ocean Salinity mission (SMOS) (Mecklenburg *et al*. 2008) • Groundwater storage estimates using platforms such as the Gravity Recovery and Climate Experiment (GRACE) (Houborg *et al*. 2012)	6.4.1 Change in water use efficiency over time 6.4.1 Level of water stress: freshwater withdrawal as a proportion of available freshwater resources 6.6.1 Change in the extent of water-related ecosystems over time
Water quality	The extent to which agriculture contributes to reduction in water quality	• Multispectral and hyperspectral estimates of physical (e.g. sediment, temperature), chemical (e.g. salinity) and biological properties (e.g. algae) (Ritchie *et al*. 2003) • Estimates of dissolved organic matter through fluorescence spectroscopy (Carstea *et al*. 2016)	6.3.1 Percentage of wastewater safely treated, disaggregated by economic activity 6.3.2 Percentage of receiving water bodies with ambient water quality not presenting risk to the environment or human health
Land use change	The impact of agricultural expansion (a measure of the environmental cost of expansion, such as loss of wetlands, habitats, forest and biodiversity)	• Agricultural monitoring systems for crop area, type, status and yield based on current optical and SAR remote sensing (Han *et al*. 2012; Yan and Roy 2014; Inglada *et al*. 2015; Lobell *et al*. 2015; Matton *et al*. 2015; Waldner *et al*. 2015; Whitcraft *et al*. 2015) • Future systems for crop monitoring based on new and forthcoming constellations offered by Planet Laboratories (Burke and Lobell 2017) and Urthecast (2017) for example • Forest monitoring systems (Hansen *et al*. 2013) • Outputs from wetland inventory mapping programs (GlobWetland 2012)	6.6.1 Change in the extent of water-related ecosystems over time 15.1.1 Forest area as a proportion of total land area 15.1.2 Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected

		• Mapping of essential biodiversity variables (EBVs) (Pereira *et al*. 2013; Skidmore *et al*. 2015)	areas, by ecosystem type 15.2.1 Progress towards sustainable forest management 15.3.1 Proportion of land that is degraded over total land area 15.4.2 Mountain Green Cover Index 15.5.1 Red List Index
Biodiversity	Conservation area per unit farm area	• The same agricultural and biodiversity mapping as above • High and very high resolution imagery from unmanned aerial and ground vehicles (UAV and UGV) (Tokekar *et al*. 2016), Planet Laboratories imagery (Frotscher *et al*. 2016; Houborg and McCabe 2016) to support more precise farm management	2.5.1 Number of plant and animal genetic resources for food and agriculture secured in either medium- or long-term conservation facilities 15.9.1 Progress towards national targets established in accordance with Aichi Biodiversity Target 2 of the Strategic Plan for Biodiversity 2011–2020
Energy use	Energy used per unit output or per hectare	• Thermal mapping (thermography) of energy losses from industrial agriculture buildings to monitor energy use efficiency (Bitelli *et al*. 2015)	7.2.1 Renewable energy share in the total final energy consumption
Greenhouse gas (GHG) emissions	Emissions per unit output	• Atmospheric monitoring of GHGs from agriculture (methane and nitrous oxide) from platforms and sensors such as Sentinel-5P / TROPOMI, Sentinel-5 and MERLIN (Butz *et al*. 2012; Veefkind *et al*. 2012; Hu *et al*. 2016; Ehret *et al*. 2017)	9.4.1 CO_2 emission per unit of value added

The enabling environment for remote sensing in a sustainable global food system

Remote sensing contributes to, and will continue to contribute to, the development of more sustainable food systems by providing information to: support farm management decisions; assess the impact of agricultural practices; and track progress towards sustainable development indicators. The degree to which this happens will depend on several technical, institutional, political and social conditions:

1. The level of readiness of the technology (to collect and process data, to store and deliver information) for timely, reliable and cost-effective large-scale implementation. The examples in the previous two sections range from operational systems to cutting-edge research in air-borne and space-borne sensor development and platform miniaturisation that will allow more accurate, detailed and frequent observations. The growth in the size and number of companies and service providers in the remote sensing sector (BCC research 2016; Global Industry Analysts 2016; Satellite Industry Association 2017) means there are more options for

implementation which should reduce the cost of acquiring the information and improve the usability of it. However, there are open questions whether technologies, such as large constellations of miniaturised platforms, can meet investor expectations by offering disruptive, yet profitable, costs per square kilometre for high-resolution imagery.

2. The generation of new validation and calibration datasets that are as extensive and representative as the new remote sensing information. The ability to map and monitor the globe on a daily time step with unprecedented levels of spatial and thematic detail in platforms such as Google Earth Engine requires new approaches to collect sufficient ground-truth data. Citizen science (Goodchild 2007), integrated ground-based sensor networks (Bröring *et al.* 2011) and the Internet of Things (Stankovic 2014) will all likely play a role in ground truthing remote observations. This increasing amount of crowdsensed data may itself become a valuable source of geospatial information in future (Toth and Jóźków 2016).
3. The development of protocols and methods for the complementary use of remote sensing alongside established means of monitoring and measuring. There are cases where remote sensing can replace existing measures (see point 4), but the most likely use is as a complementary source of information. In many instances, remote sensing information cannot replace expert knowledge in other domains, nor can it replace detailed farmer-, field- and laboratory-derived information: information that is based on decades of work to develop, refine and implement accurate and relevant measurements of the crop, its health, its environment and its management. There is a need to further develop these formal links between the remote sensing community and scientists across the agricultural sciences, through open dialogue on the needs, potential and eventual use of Earth observation data.
4. The acceptance of remote-sensing-based estimates where they are demonstrated to be superior direct replacements for estimates from established methods. Whether remote sensing is seen to complement or compete can sometimes be determined from the way its results are presented. Pixel counting to estimate agricultural area is one example where bias in the remote-sensing-based estimates is often not considered, which leads to criticism and a lack of acceptance from the statistical community (Gallego 2004). In these cases, an approach where the strengths of remote sensing are used to support and improve statistical estimates, survey based estimates or sparse, but high-quality, measurements from other networks would lead to a greater chance for its integration.
5. Increased uptake of information technology within agriculture. Agriculture has lagged behind other sectors, such as energy, in the use of big data, but investments have increased rapidly since 2013, especially in agricultural analytics for precision agriculture (Mulla 2013) and on-farm decision support (World Bank 2017, p. 403) and the opportunities to exploit it are large (Kamilaris *et al.* 2017). The proliferation of low cost mobile apps and information services that rely on remote sensing and other sources of information to deliver site specific information to farmers on water (Calera *et al.* 2017), crops (Delerce *et al.* 2016) and pest management (CGIAR 2017) also

suggests that the sector is catching up rapidly.

6. New institutional frameworks and investments to ensure the quality, coverage and access to remote sensing data in open and collaborative systems, which may involve both the public and private sector (IEEE-USA 2016). These systems will need to leverage ground-, air- and space-borne sensor networks, and the support communication between those networks, to fill data gaps and reduce costs. This needs to happen in the developed world and in emerging economies, otherwise the digital divide between them will only increase. As remote sensing becomes part of the big data revolution, there are concerns that the technology to manage and deliver big data are in the hands of a small number of multinational companies.
7. Ethics and governance issues, including data ownership, privacy, security, responsibility and liability (Wolfert *et al.* 2017). For example, there are large differences in national policies regarding the acceptable use of UAV platforms to collect highly detailed spatial data. There are also large differences in national arrangements regarding remote sensing data: some have adopted open data initiatives or have already integrated remote sensing into their development planning operations or sectoral growth programs, while others have not. Moving towards more open data often requires substantial changes in culture within an organisation or government, with solid value propositions for doing so.
8. Building the capacity of practitioners in government, development agencies and the private sector (including smallholder farmers) to use, analyse and interpret current and emerging sources of remote sensing information. Earth observation, spatial data and geo-information science already contribute to daily lives through weather forecasts and mobile mapping applications, for example, but there is still a large knowledge gap between this use and the understanding of the underlying spatial information. As the technology to acquire information and deliver services develops, so must the coordination of education and development activities, which will require innovative programs to strengthen the capacity of individuals and networks. This need aligns with the mission of the Faculty of Geo-Information Science and Earth Observation, University of Twente. Since its inception in 1950 (when it was called the International Training Centre), ITC has trained over 25 000 students, most of them from the global south. ITC has also developed a global network of partners to develop capacity and remedy skill shortages in less developed countries, to use geospatial solutions to deal with national and global problems such as the need for sufficient and secure food production.

Remote sensing is already contributing to a more sustainable global food system. The Global Agricultural Monitoring (GEOGLAM) Crop Monitor (https://cropmonitor.org) is one excellent example of how different remote sensing datasets and national expert knowledge can be brought together to aid policy makers through information that monitors crop production, the weather and markets.

GEOGLAM was launched in 2011 following a G20 meeting of agricultural ministers as part of a G20 Action Plan on Food Price Volatility. GEOGLAM coordinates satellite-monitoring observation systems to enhance crop production projections and weather forecasting data and harmonise them. GEOGLAM also provides a framework to strengthen capacity to produce and disseminate forecasts of agricultural production using Earth observation data.

The GEOGLAM Crop Monitor provides regular reports on global crop condition to support the Agricultural Market Information System or AMIS (http://www.amis-outlook.org), which is an inter-agency platform to enhance food market transparency and policy response for food security. AMIS assesses the global food supply for major crops such as wheat, maize, rice and soybeans and provides a platform to coordinate policy action in times of market uncertainty. Together, the GEOGLAM Crop Monitor and AMIS provide monthly bulletins that provide early warning on crop conditions and trends in global markets.

The initiative has been successful because it has built upon existing monitoring programs and strengthened them by clearly demonstrating the value of combining Earth observation data, ground observations and expert knowledge. It has also established a research-to-operation cycle that includes the development of training materials and guidance documentation and the promotion of best-practices around capacity development for remote sensing. It is an encouraging example of the role remote sensing can play in a more food secure future.

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Endnotes

1 LiDAR is used as an acronym for 'light detection and ranging'.

2 Radar or RADAR stands for 'radio detection and ranging'.

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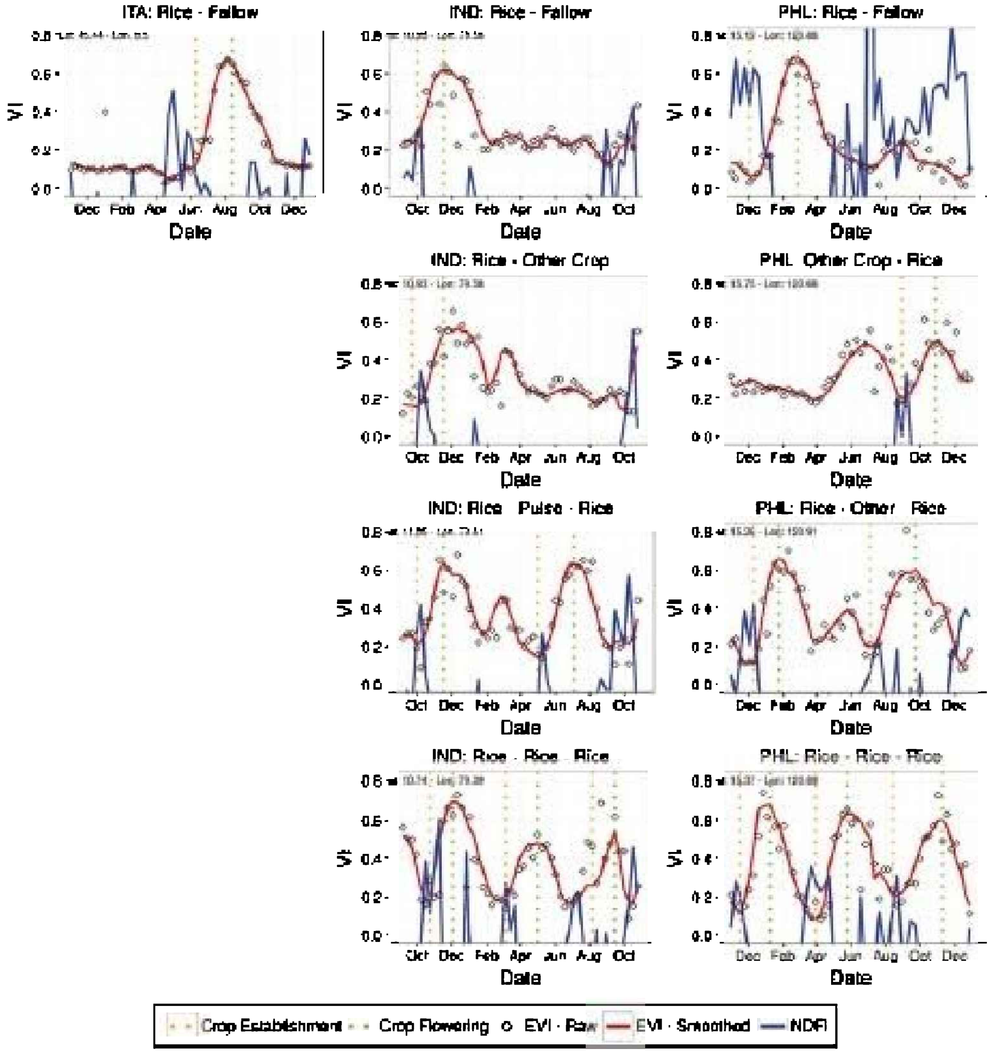

Plate 19.1. The temporal signature of vegetation (original data represented by black circles and the smoothed signal in red) and water (blue) based on MODIS imagery in Italy, India and the Philippines from nine different rice-based systems. Source: Reprinted from Remote Sensing of Environment, Vol 194, Boschetti M, Busetto L, Manfron G, Laborte A, Asilo S, Pazhanivelan S, Nelson A. PhenoRice: A method for automatic extraction of spatio-temporal information on rice crops using satellite data time series, p347–365, doi:10.1016/j.rse.2017.03.029. Copyright (2017), with permission from Elsevier.

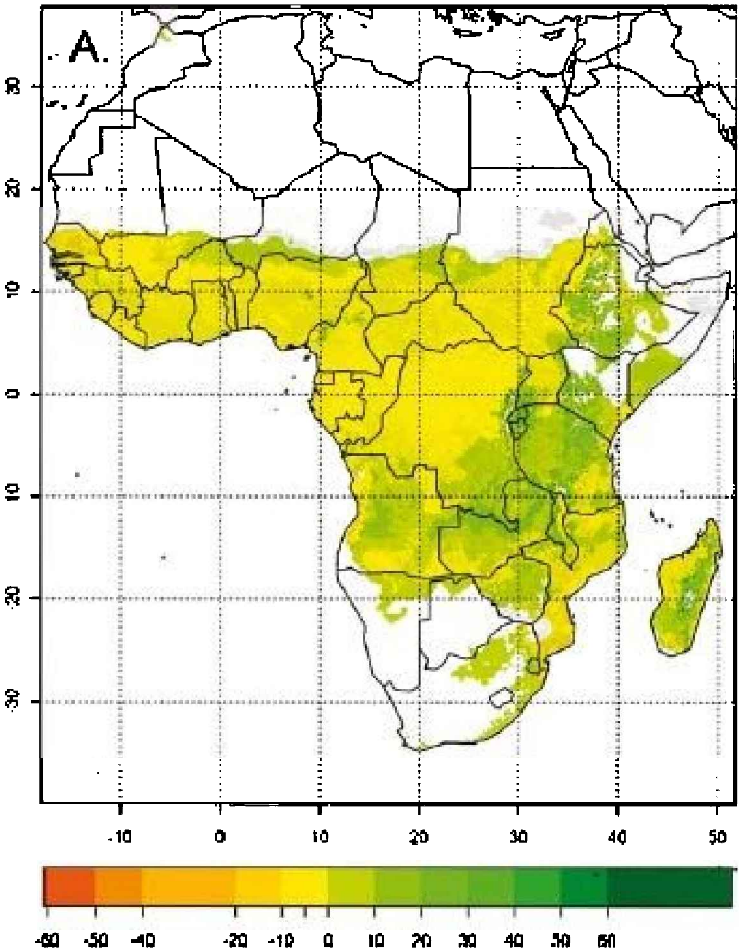

Plate 19.2. Future impact of climate change on cassava suitability in Africa expressed as the percentage change in climate suitability. Areas showing a reduction in suitability are in orange and yellow while areas with increased suitability are green. Suitability is overlaid on croplands in grey. Source: Reprinted by permission from RightsLink Permissions Springer Customer Service Centre GmbH: Springer US, Tropical Plant Biology (https://link.springer.com/journal/12042), Vol 5, Is Cassava the Answer to African Climate Change Adaptation?, Jarvis A, Ramirez-Villegas J, Campo BVH, Navarro-Racines C, p9–29. doi:10.1007/s12042-012-9096-7. Copyright (2012).

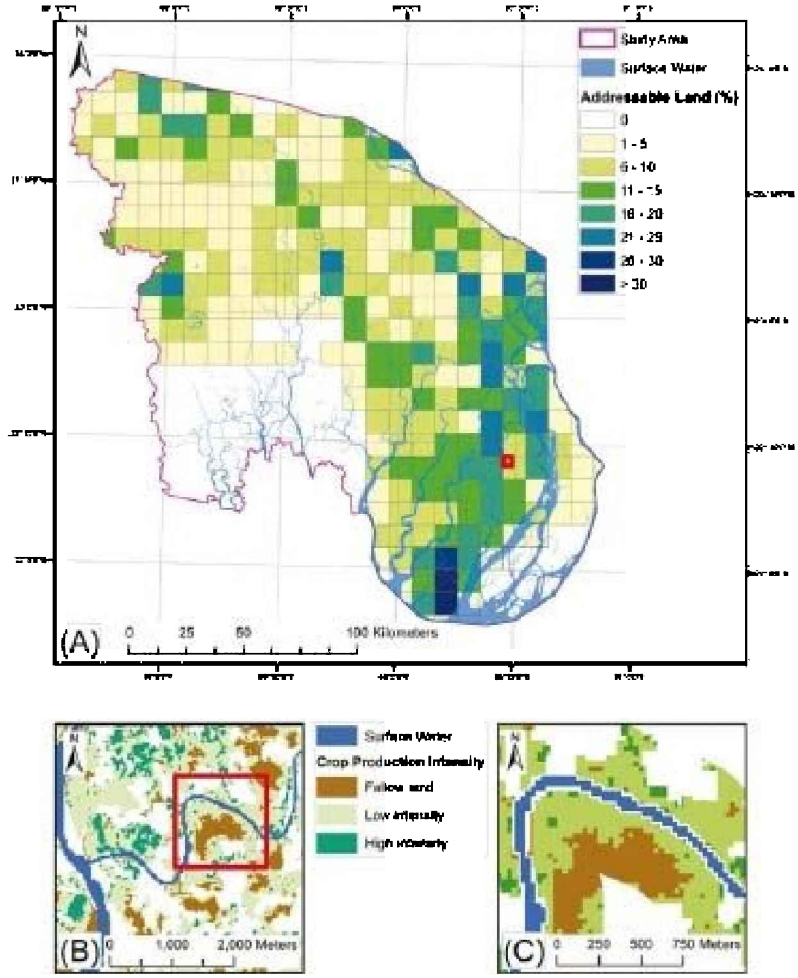

Plate 19.3. (A) Agricultural land suitable for surface water irrigation expressed as percentage of total cropland area. **(B)** Detail depicting a block of low-production intensity and fallow land proximal to surface water. **(C)** Further detail depicting a 385 m buffer indicating precise locations of fallow and low-intensity cropland upon which surface water irrigation could be used. Source: Reprinted from Land Use Policy, Vol 60, Krupnik TJ, Schulthess U, Ahmed ZU, McDonald AJ Sustainable crop intensification through surface water irrigation in Bangladesh? A geospatial assessment of landscape-scale production potential, p206–222, doi:10.1016/j.landusepol.2016.10.001, under a Creative Commons Attribution Licence (CC BY) http://creativecommons.org/licenses/by/4.0.

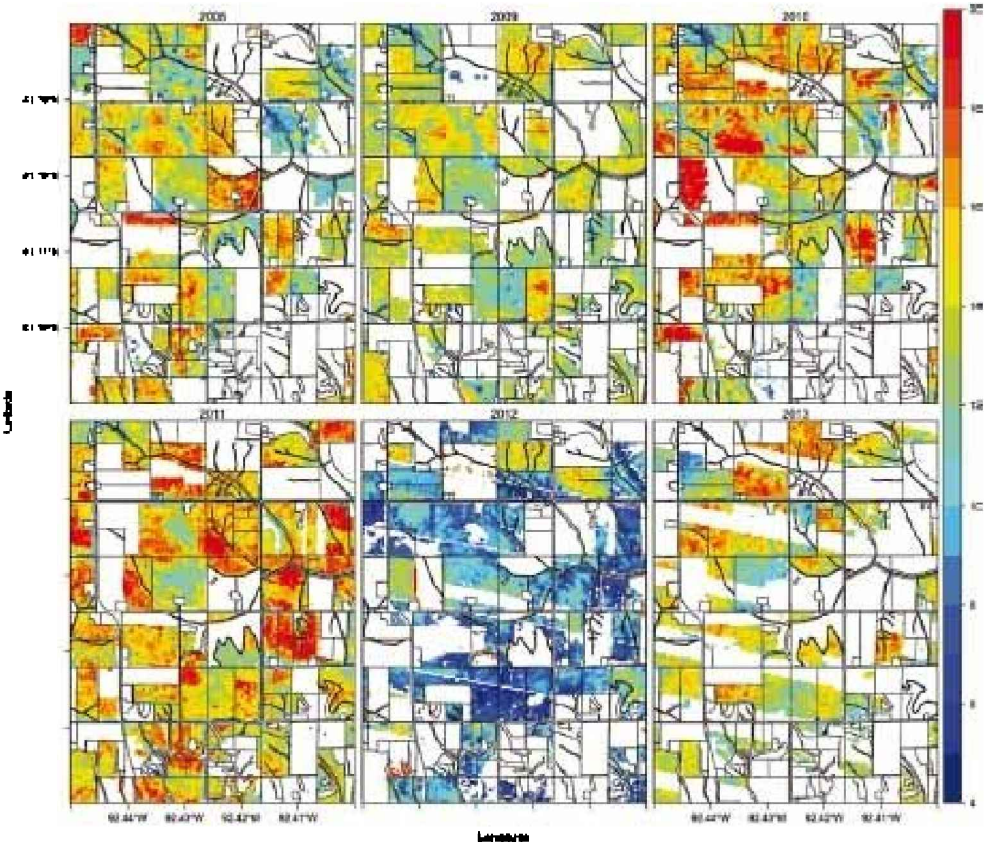

Plate 19.4. High spatial resolution maize yield estimates for 2008–2013 in a part of Poweshiek County, Iowa. Legend shows maize yields in t/ha. Source: Reprinted from Remote Sensing of Environment, Vol 164, Lobell DB, Thau D, Seifert C, Engle E, Little B. A scalable satellite-based crop yield mapper, p324–333, doi:10.1016/j.rse.2015.04.021, Copyright (2015), with permission from Elsevier.

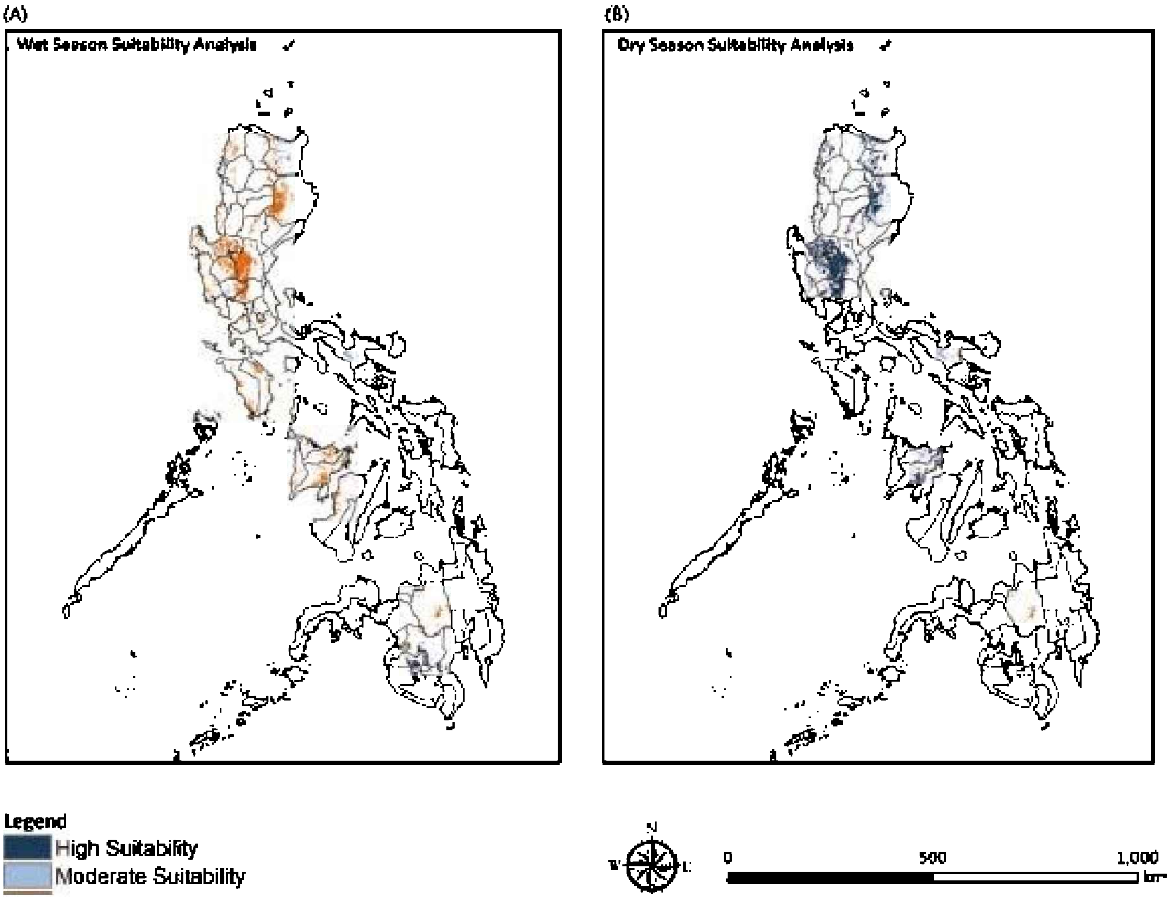

Plate 19.5. The rice growing extent of the Philippines estimated to be climatically suitable for AWD in **(A)** wet harvest season and **(B)** dry harvest seasons in the Philippines. Source: Reprinted from Carbon Management, Vol 8, Sander BO, Wassmann R, Palao LK, Nelson A. Climate-based suitability assessment for alternate wetting and drying water management in the Philippines: a novel approach for mapping methane mitigation potential in rice production, p331–342, doi:10.1080/17583004.2017.1362945, under a Creative Commons Attribution-NonCommercial-NoDerivatives Licence http://creativecommons.org/licenses/by-nc-nd/4.0.