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Remote sensing for agricultural applications: A meta-review

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ABSTRACT

Agriculture provides humanity with food, fibers, fuel, and raw materials that are paramount for human livelihood. Today, this role must be satisfied within a context of environmental sustainability and climate change, combined with an unprecedented and still-expanding human population size, while maintaining the viability of agricultural activities to ensure both subsistence and livelihoods. Remote sensing has the capacity to assist the adaptive evolution of agricultural practices in order to face this major challenge, by providing repetitive information on crop status throughout the season at different scales and for different actors. We start this review by making an overview of the current remote sensing techniques relevant for the agricultural context. We present the agronomical variables and plant traits that can be estimated by remote sensing, and we describe the empirical and deterministic approaches to retrieve them. A second part of this review illustrates recent research developments that permit to strengthen applicative capabilities in remote sensing according to specific requirements for different types of stakeholders. Such agricultural applications include crop breeding, agricultural land use monitoring, crop yield forecasting, as well as ecosystem services in relation to soil and water resources or biodiversity loss. Finally, we provide a synthesis of the emerging opportunities that should strengthen the role of remote sensing in providing operational, efficient and long-term services for agricultural applications.

1. Introduction

The World Summit on Food Security declared that in 2050, "The world's population is expected to grow to almost 10 billion by 2050, boosting agricultural demand - in a scenario of modest economic growth - by some 50 percent compared to 2013" (FAO, 2017). However, this increase in food production must be accompanied by a sustainable management of agricultural lands to stop or at least slow down the negative impacts on the quality and quantity of water and soil resources, land degradation, green-house gas emissions, or biodiversity (Gomiero et al., 2011). The conversion from intensive to sustainable agriculture must be conducted in the context of global change, by considering unexpected climatic conditions (e.g. change in temperature and precipitation patterns) or extreme climatic events (Tirado et al., 2010). This conversion is also likely to be strongly driven by energetic transition since biofuels may become a significant source of energy (Demirbas, 2009) while farming activities will have to be relocated to optimize transport and production costs.

In the light of this challenging context for agriculture, there is a strong requirement for monitoring crop growth and status in various locations and environmental contexts, with various temporal resolutions, and for different purposes. Near-real time monitoring is needed to react to extreme events according to the changing climatic conditions, and thus to minimize their impact on the global food system (Wheeler and von Braun, 2013), but also to optimize management practices in a sustainable way by optimizing externalities (Areal et al., 2018). Economic returns drive a high pressure to provide short-term yield prediction at the global, regional and farm scale. However, such predictions are also highly valuable to efficiently anticipate food production shortages and thus ensure food security in the most vulnerable regions of the world (Di Falco et al., 2012). In a longer-term perspective, lessons learned from monitoring and forecasting specific cultivars in given locations and climatic conditions can be very instructive to assist the adaptation of cultural practices in the same places with different climatic conditions or in other places with similar expected climatic conditions. Remote sensing appears as an essential tool to respond to the above-mentioned requirements since it offers a non-destructive mean of providing recurrent information from the local to the global scale in a systematic way, thereby enabling the characterization of the spatiotemporal variability within a given area.

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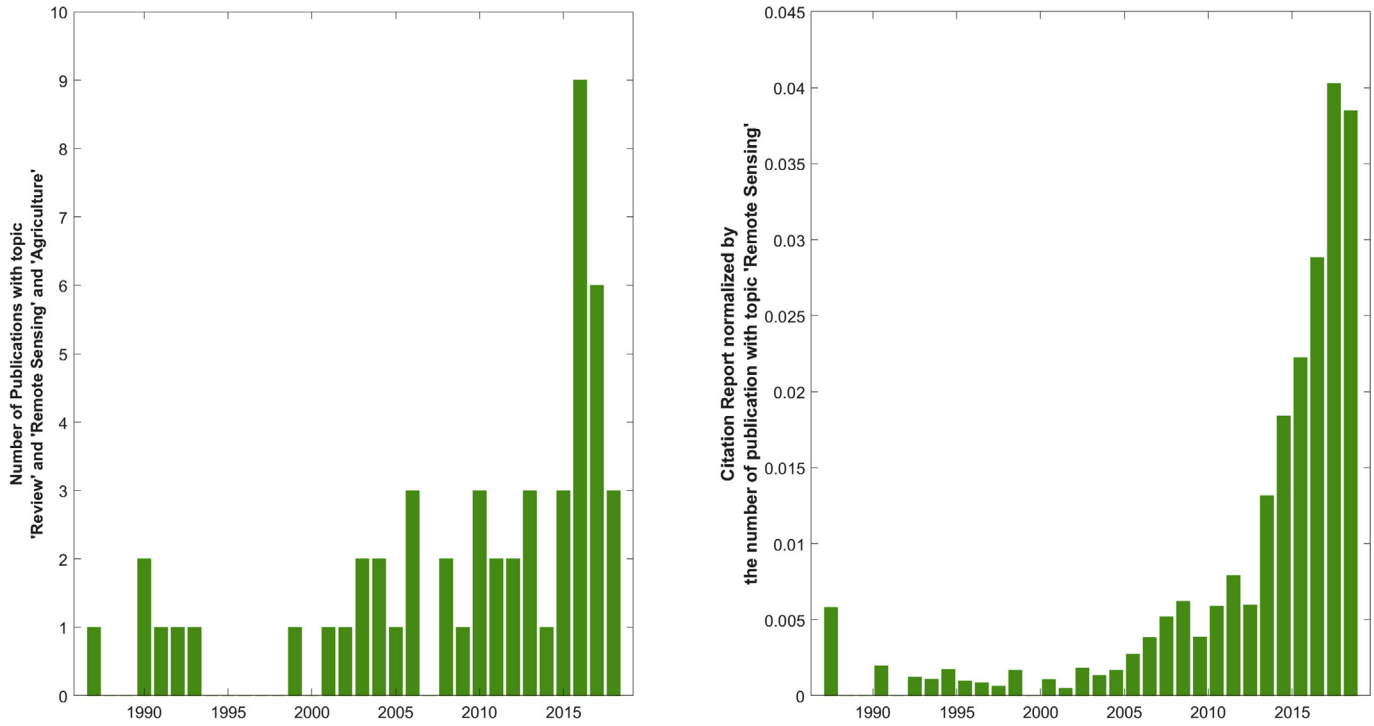


Fig. 1. Web Of Science search results using the Web of Science Core collection database (November 2018): Left: number of publications including the topic: agriculture (AND) review (AND) remote sensing from 1987 to 2018. Right: Citation report of these publications throughout the years: for each year, the number of citations is normalized by the total number of publications searched with the single topic "remote sensing".

Monitoring agriculture from remote sensing is a vast subject that has been widely addressed from multiple viewpoints, sometimes based on specific applications (e.g. precision farming, yield prediction, irrigation, weed detection), on specific remote sensing platforms (e.g. satellites, Unmanned Aerial Vehicles –UAV-, Unmanned Ground Vehicles -UGV-) or sensors (e.g. active or passive sensing, wavelength domain, spatial sampling) or specific locations and climatic contexts (e.g. country or continent, wetlands or drylands). The growing number of published literature shows that remote sensing for agriculture has now reached a certain level of knowledge (Fig. 1, left) and that the interest in agricultural applications is exponentially growing, especially since 2013 (Fig. 1, right). This increasing literature also reflects the substantial progress in relevant technology that has emerged, including numerous sensors with unprecedented combinations of spatial, temporal and spectral capacities (e.g. Sentinels, Gaofen), the advent of small new platforms such as nano-satellites or UAV, and the deployment of cloud computing and machine learning techniques. These technological improvements should allow meeting the long-lasting expectations for remote sensing applied to agriculture.

The present work aims at complementing previous efforts by taking a tour across this wide topic with the intention to serve as a meta-review, dedicated to both people interested in using remote sensing for agricultural applications and to the remote sensing community as a whole. We do not linger on specific comparisons between methods or results, nor do we recommend any single best way of using remote sensing for agriculture. Instead, the scope is to provide a thorough overview on what remote sensing has to offer for agricultural applications, while redirecting the readers to more specific reviews or papers when necessary by citing the major references, and preferably the most recent ones. This paper is divided in three main sections. The first one provides an outline of the current remote sensing techniques that are relevant for the agricultural context. It presents the agronomical variables and plant traits that can be estimated by remote sensing, and describes the empirical or deterministic approaches to retrieve them. The second part of this paper focuses on the way remote sensing contributes to answer to the specific requirements of different stakeholders for several key agricultural applications. Finally, we provide a synthesis of the emerging opportunities that should strengthen the role of remote sensing in providing operational, efficient and long-term services for agricultural applications.

2. Extracting agricultural information from remote sensing

2.1. From available observations to targeted variables: the overarching idea

Remote sensing is the acquisition of information about an object or phenomenon from distance. This involves an instrument or a sensor mounted on a platform, such as a satellite, an aircraft, an UAV/UGV, or a probe. The sensor typically measures the electromagnetic radiation that is either reflected or emitted by the target. The type of information accessible from remote sensing depends on the specific properties of the instrument and its platform. These properties include: satellite orbitography, UAV/UGV motion plan, field sensor position and orientation, active or passive sensing, detector array and optical lens characteristics, as well as storage capabilities. The sensor/platform features define the spectral, directional and polarization capabilities, the spatial resolution and revisit frequencies, as well as the signal-to-noise ratio. Furthermore, they indirectly influence the illumination and atmospheric conditions during data acquisition. Therefore, to be able to detect and quantify changes at the Earth's surface, the different artefacts inferred by the measurement conditions and sensor characteristics must be taken into account so that the remaining signal only depends on the target radiative properties (Roy et al., 2002).

In the field of agriculture, the information of interest consists of traits or features of the agricultural systems, and especially how these latter vary in space and time. Nock et al. (2016) defined functional traits as morphological, biochemical, physiological, structural, phenological or behavioral characteristics that influence organism performance or fitness. They defined variables as traits or characteristics that vary from one individual (a plant), group (a crop) or society (an area) to

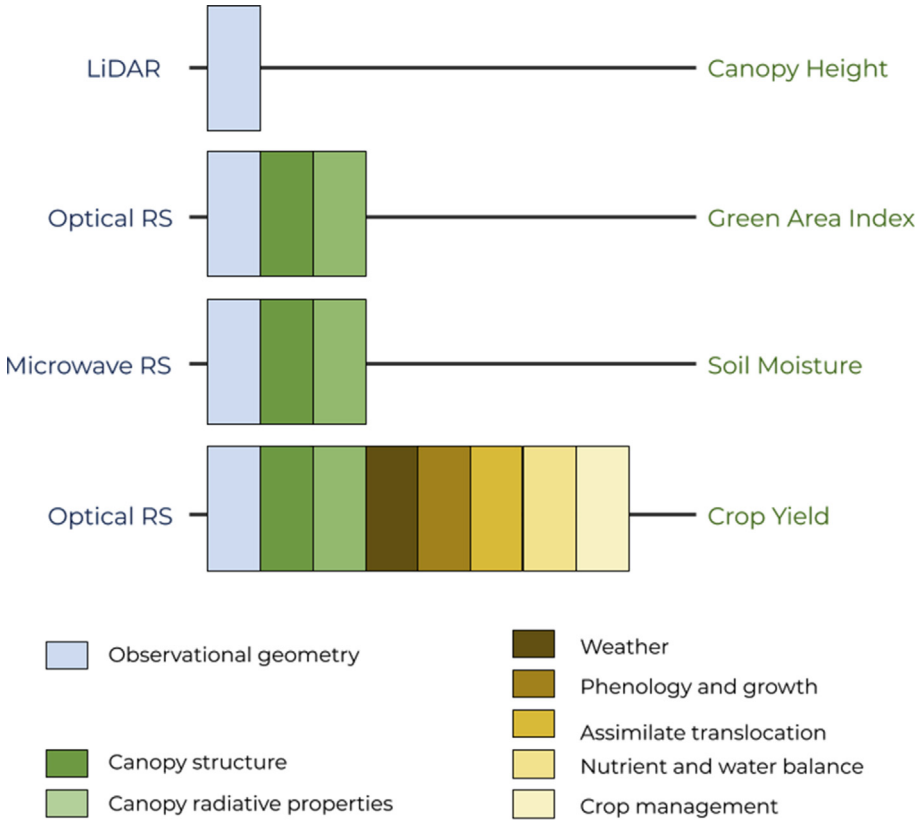


Fig. 2. Schematic representation of the level of complexity of the links between remote sensing observations (on the left) and selected agronomic traits of interest (on the right). In the context of this paper, crop height and green area index are considered as primary variables (directly involved in the radiative process) while crop yield is a secondary variable (indirectly accessible from remotely sensed observations). The boxes represent driving factors of different nature that influence this relationship. Optical remote sensing refers to remote sensing over the solar and thermal infrared spectral domains.

another individual, group, or society. The nature of these agronomic traits can be typological (e.g. crop type), physical (e.g. crop canopy temperature or soil moisture), chemical (e.g. leaf nitrogen content), biological (e.g. crop phenology), structural (e.g. leaf inclination), or geometrical (e.g. plant density). Some traits of interest, such as crop productivity, can result from a series of intertwined biophysical processes during a given temporal window (e.g. crop growth cycle).

It is important to notice that none of these traits are directly measured by remote sensing instruments. The relationship between what is measured (i.e. radiance) and the traits themselves needs to be somehow modelled in order to infer the later from the former. Depending on the trait, this level of modelling can be more or less substantial (Fig. 2). For example, relating a trait such as canopy height to LiDAR (Light Detection And ranging) measurements is only a question of geometry: that of the path of the photon beam reflected by the canopy. Relating the area of green leaves in a canopy (known as green area index or GAI) to measurements over the solar spectral domain (400 nm–2500 nm) involves questions related to the geometry, as well as to the canopy structure (leaf inclination and position, density and shape), and the radiative properties of the canopy elements (e.g. reflectance and transmittance as driven by the biochemical composition of the leaves, stem). Crop yield can also be linked to remote sensing observations, but this further involves to characterize driving factors related to atmospheric forcing (e.g. solar radiation, air temperature and humidity, wind speed, precipitation), vegetation functioning (e.g. phenological stages and growth, transpiration and photosynthesis, redistribution of assimilates within plant organs), and crop management (e.g. nutrient and water supplies, pruning).

As discussed further in detail, bridging the gap between the physical remote sensing measurement and the agronomic trait can be done using empirical or mechanistic approaches, or the combination of both. Empirical models refer to models that directly relate inputs to outputs by pure statistical means while mechanistic models focus on the causality between inputs and outputs by describing the different mechanisms involved (Baker et al., 2018). In practice, the main difference is that mechanistic approaches rely on assumptions and models while empirical ones require data acquisition. Depending on the process and the agricultural application, one approach may be more suited while either mechanistic or empirical approaches can be used to characterize the same trait. For example, crop yield can be estimated either empirically with simple vegetation indices derived from satellite reflectances or mechanistically by combining remotely sensed GAI with process-based crop growth modelling. The advantage of the former solution lies in its simplicity, but it comes at a cost of collecting ground data (e.g. yield and reflectances) and a probably lack of extrapolation capacity in time and space. The latter offers explanatory capacity due to its deterministic modelling, but it requires assumptions that may not be guaranteed, leading to an increase in uncertainty.

The following sections present in details how traits can be estimated from remote sensing observations. In this paper, we will mainly refer to the term ‘variables’ as remote sensing allows characterizing the variation of traits in space and time. Table 1 provides a summary of the principal variables in relation to the type of remote sensing data that are typically used to retrieve them. We make the distinction between primary variables, *i.e.* variables that can be directly addressed from remote sensing since they are involved in the process of radiative transfer based on current scientific knowledge (e.g. Green Area Index, surface temperature, soil moisture), and secondary variables (e.g. crop yield, evapotranspiration) that depend on the combination of one or several underlying factors, some of them may not being derived from any remote sensing data.

2.2. Retrieving primary variables: agronomic variables directly involved in the radiative transfer process

Estimating crop characteristics from remote sensing is not an easy task due to the ill-posed nature of the problem: the available information is constrained by the sensor and platform capacities (few

Table 1
Main primary variables that can be retrieved from remote sensing data. This list is not intended to be exhaustive. The number of crosses is proportional to the relative levels of both maturity and accuracy found in the literature to retrieve the given variable from the considered spectral domain. An empty cell indicates that the variable cannot be retrieved from the given spectral domain or that no relationship was yet investigated. LAI stands for Leaf Area Index, i.e. half the total surface of leaves per unit ground horizontal area. fAPAR and fIPAR stand for the fraction of Absorbed or Intercepted Photosynthetically Active Radiation (PAR domain: 400–700 nm).

Primary Variables	Solar domain				Thermal Domain	Microwave Domain	
	Passive			Active	Passive	Passive	Active
	Multi/Hyper spectral	Fluorescence	Photogrammetry	LIDAR			
Plant Density Organ counting	+ + +						
GAI/LAI	+ + +			+ +		+	+
Green Cover Fraction	+ + +			+ +			
Leaf Biochemical Content	+ + +	+ +					
Leaf Orientation	+ +		+ + +	+ + +			
Height			+ + +	+ + +			
fAPAR-fIPAR	+ + +	+		+ +			+
Albedo	+ + +						
Temperature (vegetation/soil)					+ + +		
Soil moisture	+ +				+ + +	+ + +	+ + +
					+ + +		

wavelengths, few viewing directions, and limited spatiotemporal information), and the measured data are affected by noise, which does not ensure the uniqueness and the stability of the solution (Baret and Buis, 2008; Wang, 2015; Jacob et al., 2017).

Many approaches have been tested to retrieve agricultural variables from remote sensing data. We classified them in three categories: (i) purely empirical methods that consist of directly calibrating a relationship between the measured signal to the variable of interest (e.g. linear and nonlinear regressions, machine learning), (ii) mechanistic methods that consist of inverting models based on the radiative transfer theory (for solar and microwave domains), Maxwell's equations (for radar interferometry and polarimetry), optical and projective geometry (for LIDAR and photogrammetry), and (iii) "contextual methods" that take advantage of spatial and temporal properties within the images.

2.2.1. Purely empirical methods

Purely empirical approaches, also named as "regressions", consist of calibrating a numerical relationship between one or several measured biophysical variables and the remote sensing signal or a numerical transformation of this signal (using vegetation indices for instance, for an exhaustive list of such indices see Henrich et al. (2009)). The simplest examples are linear or nonlinear relationships established between: (i) reflectances and Leaf Area Index (Viña et al., 2011), fraction of Absorbed Photosynthetically Active Radiation (Dong et al., 2015), chlorophyll (Gitelson et al., 2005), or water content (Chen et al., 2005); (ii) backscattering coefficient and LAI, crop water content, or crop height (McNairn and Shang, 2016); and (iii) LIDAR and chlorophyll content (Eitel et al., 2014). More advanced techniques include machine learning regression such as support vector machine (Mountrakis et al., 2011), random forest (Zhu and Liu, 2015), or Gaussian processes and neural networks (Camacho et al., 2017; Yuan et al., 2017). Compared to linear or non-linear regressions, such approaches allows to statistically characterize complex relationships between variables while they do not have to be explicitly formalized. They generally require a significant calculation time during the training step but they permit real-time computations in forward mode, which is of strong interest for agricultural applications.

Purely empirical relationships are typically calibrated over experimental observations and thus are constrained by the representativeness of the calibration dataset. This makes the empirical relationship sensitive to the conditions of acquisition, including atmospheric conditions and geometry of acquisition (Epiphanio and Huete, 1995), to the crop conditions, e.g crop type, water status or phenological stages (Colombo et al., 2003; Gitelson, 2004), or specific features such as the geomorphological context (Matsushita et al., 2007). Furthermore, it is necessary to account for the uncertainties associated to both the ground based measurements of the biophysical variable and the remote sensing signal. These uncertainties include the noise and errors associated to the devices (Fernandes and G. Leblanc, 2005), as well as the spatial sampling strategy in relation to the observation footprints of the measurements (Bellvert et al., 2014).

2.2.2. Mechanistic methods

Physically-based models have been designed to simulate the radiative transfer of the signal within a canopy from a description of its architecture and the properties of its constituents. The use of a physically-based model implies that the retrieved variable is either directly used as input to the model (for example, LAI, soil moisture, channel emissivity and surface temperature) or is simulated by the model (e.g. green fraction, fAPAR).

Physically-based models have been developed within each wavelength domain, respectively to the underlying theory: radiative transfer theory over the solar, thermal and microwave domains, and Maxwell's equations for radar interferometry and polarimetry. Over the optical and microwave domains, numerous Radiative Transfer Models (RTM) were developed from the most simple 1D description of the canopy architecture up to much more complex 3D mock-ups. For a comprehensive description and benchmarking of such models in the solar spectral domain, the reader is referred to the RAMI exercise (Radiative Transfer Model Intercomparison (Widlowski et al., 2015),). LIDAR simulations from 3D mock-ups were also proposed by several authors (Ristorcelli et al., 2014; Gastellu-Etchegorry et al., 2015). In the thermal infrared domain, the reader is referred to Jacob et al. (2008) and Cao et al. (2019) who reviewed the existing models for temperature retrieval or data normalization. A short description with appropriate references to the different existing models in the passive microwave domain is proposed by Wigneron et al. (2003). In the active microwave domain (Synthetic Aperture Radar, SAR), models rely either on the radiative transfer theory (Erten et al., 2016) or on Maxwell's equations (e.g. water cloud model) (Bériaux et al., 2015).

Model inversion consists of finding the best match between the signal simulated by the model and the measured one by minimizing a

cost function. The latter is derived from the maximum likelihood theory and should account for the model and measurement uncertainties (Baret and Buis, 2008). Two types of methods can be considered whether the cost function is computed using the signal value (e.g. optimization and look-up tables) or the variable of interest (e.g. machine learning approaches) (Jacquemoud et al., 2009).

- Optimization techniques are iterative methods. They start from an initial guess of the model parameters to converge towards an optimal set of parameters through the minimization of a cost function computed between the measured and simulated signal. Classical optimization methods, based on iterative steepest descent algorithms are generally sensitive to the initial guess of the solution in relation to the existence of local minima of the cost function (Baret and Buis, 2008; Wigneron et al., 2017). Some techniques have been also developed to avoid this problem, such as Markov Chain Monte Carlo that provide posterior probability distributions of the variables (Zhang et al., 2005), or genetic algorithms that avoid the initial guess issue by systematically scanning the whole set of possibilities (Fang et al., 2003; Lopez-Sanchez et al., 2007). Optimization techniques are flexible in terms of number of inputs and easily adaptable to any set of configuration measurements since they do not require pre-computation. However, regardless of the algorithm, they are demanding in computer resources and time, and are thus hardly used in an operational context. The computing time can be partly decreased by using the adjoint model that provides an analytical expression of the cost function (Lavergne et al., 2007; Lauvernet et al., 2008; Qin et al., 2008).
- Look-Up-Table (LUT) techniques consist of computing the cost function and finding its minimum over a large dataset composed of the simulated signal and the corresponding model inputs. If the LUT is sufficiently well sampled in the space of the canopy variables, this method is not sensitive to local minima (Combal et al., 2002). It has been operationally implemented and widely used over the solar domain (Weiss et al., 2000; Myneni et al., 2002; Houborg et al., 2009; Rivera et al., 2013; Danner et al., 2017), the microwave domain (Merzouki et al., 2011) and LIDAR based sensing (Hmida et al., 2017). Although it can be time demanding during the preliminary step of the LUT construction depending on the number of simulations and the complexity of the model, the minimization of the cost function is very fast. The method is thus well adapted in an operational context (Verger et al., 2014b), except that, conversely to optimization techniques, LUT are not flexible since changing the waveband or the configuration geometry implies running new simulations.
- Similarly to purely empirical methods, machine learning can be trained over a learning data set issued from a physically based model (Verrelst et al., 2018). Using simulated datasets rather than measurements can ensure a better sampling of the range of conditions that can be observed by the sensors, including the vegetation type and state (e.g. phenology, stress), type of background (e.g. soil, understory) and state (e.g. moisture, roughness), or geometry of observation. However, the learning dataset is limited by the ability of the model to correctly simulate the actual signal. Machine learning has been successfully used to invert physically-based models in the agricultural context since the early 2000's by using neural networks with a sampling of the input variable space adapted to the targeted vegetation type (Weiss et al., 2002; Fang and Liang, 2004; Frate et al., 2004; Duveiller et al., 2011b; Claverie et al., 2013; Ermida et al., 2017). Other machine learning algorithms, such as Support Vector Machine or Gaussian Processes have been used since (Rivera et al., 2015; Camps-Valls et al., 2016). However, the performances of the machine learning method are closely linked to the ability of the RTM to appropriately simulate the reality, and thus, to the associated uncertainties and biases. Another difficulty when using machine learning on model simulations concerns the sampling strategy of the distribution and co-distribution of the model input variables to well represent the variability (Bacour et al., 2002).

Conversely to the solar and microwave domains, the inversion of complex models based on radiative transfer or geometrically based have almost received no attention in the thermal domain, because of complexities induced by the spatiotemporal variability of land surface temperature (Lagouarde et al., 2013). Therefore, most studies have focused on inverting simple equations to retrieve end-member temperatures such as composite temperature for a homogeneous target, soil and vegetation component temperatures, or sunlit and shaded component temperatures (Jacob et al., 2004, 2017; Li et al., 2013; Bian et al., 2016, 2017). Recent studies investigated the inversion of parametric (i.e. kernel driven) models in order to characterize angular signature, to further derive component temperatures from inversion procedure, or to normalize off-nadir measurements (Duffour et al., 2016; Ermida et al., 2017, 2018).

Finally, another kind of mechanistic approach uses the intrinsic properties of the signal to estimate crop height or to reconstruct the 3D vegetation structure. This includes (i) stereovision/photogrammetric methods (e.g. structure from motion algorithms (Madec et al., 2017; Walter et al., 2018)) that reconstruct the geometry of the target from images acquired over the same pixel with different viewing conditions, (ii) LIDAR signal processing of laser pulse backscattering, which relies on the time-of-flight principle, and allows computing the distance to the canopy elements from the elapsed time between transmitted and return laser signals and energy (Rosell and Sanz, 2012), and (iii) interferometric SAR (InSAR), which combines the phase and amplitude of two backscattered microwave pulses separated by a given distance to determine the 3D architecture of the canopy (Erten et al., 2016).

2.2.3. Methods exploiting the spatiotemporal information

This category of methods encompasses the classification (e.g. pixel-based) and segmentation (e.g. Object-Based Image Analysis or OBIA) techniques developed for land use and land cover mapping at regional or global level, as well as for precision farming in proximal sensing (weed and disease detection). For more information on these techniques, the reader can refer to recent reviews from Blaschke et al. (2014) and Ma et al. (2017) for OBIA methods and to Tuia et al. (2011), Behmann et al. (2015), Belgiu and Drăgut (2016) and Gómez et al. (2016) for classification methods. Other applications such as object identification (e.g. rows, plant counting) relies on mathematical morphology or texture transforms such as wavelet analysis (Celik and Ma, 2010; Sakamoto et al., 2014) or Fourier transforms (Delenne et al., 2008) in space and/or time.

The spatiotemporal information can also be exploited jointly with model inversion approaches. While most of the studies dealing with the inversion of physically-based models focus on a single pixel without considering its spatial or temporal context, few of them explored the use of such information to constrain the inversion by considering that the model variables do not vary the same way in time and space (Lauvernet et al., 2008; Pierdicca et al., 2010; Atzberger and Richter, 2012).

2.3. Retrieving secondary variables: agronomic variables indirectly linked to radiative transfer

In this paper, we defined secondary variables as those that cannot be directly related to the radiative transfer mechanisms involved in remotely sensed observations. Such variables can be state variables such as water or nitrogen status related to plant functioning (e.g. growth, water and nitrogen balance). They result from the combination of several processes within the soil-plant-atmosphere continuum, and thus, indirectly drive the radiative transfer.

Similarly to primary variables, numerous secondary variable

retrieval methods have been developed with different levels of complexity, including empirical and deterministic approaches. Empirical approaches offer the advantage of directly inferring the secondary variables. For example, vegetation indices over the solar spectral domain were used to estimate crop yield (Johnson et al., 2016) and Gross Primary Production (GPP), canopy radiation use efficiency (Garbulsky et al., 2011), crop coefficient (Glenn et al., 2011), as well as crop nitrogen content (Clevers and Gitelson, 2013; Delloye et al., 2018), which was also investigated using the fluorescence signal (Tremblay et al., 2012), while the near infrared domain was mainly used to detect crop water stress (Bellvert et al., 2014).

Deterministic approaches dedicated to the estimation of secondary variables involve the use of land surface process models that depict the vegetation functioning along with related energy and matter fluxes. These models describe at least one process involving a primary variable accessible from remote sensing (e.g. GAI for crop phenology or temperature for water balance) that may be combined with other processes (e.g. water stress) to assess the secondary variable (e.g. evapotranspiration).

The retrieval of a secondary variable often requires the exploitation of different sources of information, which encompass the fusion of data provided by different sensors and over different spectral domains (Ahmad et al., 2010; Belgiu and Drăguţ, 2016; Singh et al., 2016; Guan et al., 2017), as well as ancillary information related to the functioning of the soil-plant-atmosphere continuum (Hassan-Esfahani et al., 2015; Jeong et al., 2016; Park et al., 2016; Kern et al., 2018), meteorological information (Johnson, 2014) or phenology (Bolton and Friedl, 2013).

As the main challenges in developing empirical approaches are addressed previously (section 2.2.1) and does not depend on the type of retrieved variable, we only focused on describing deterministic approaches. We present first the deterministic approaches that allow the estimation of secondary variables by combining land surface process models and remote sensing data. Then, we address more operational approaches that make use of spatial or temporal contrasts contained in the imagery (e.g. contextual approaches) to retrieve secondary variables.

2.3.1. Modelling approaches

Dealing with agricultural applications implies understanding the soil-crop functioning along with energy and matter fluxes. This includes the following processes (Brisson et al., 1998): light use efficiency and assimilate partitioning, energy balance (e.g. radiative, conductive and convective exchanges), water balance (e.g. rainfall/irrigation partitioning between runoff and infiltration, drainage, soil evaporation and vegetation transpiration), carbon balance (e.g. plant photosynthesis and respiration, litter decomposition, soil respiration), and nitrogen balance (e.g. fertilization, mineralization, denitrification, volatilization, leaching, plant nitrogen uptake and symbiotic dinitrogen fixation when applicable). All of these processes and above-mentioned components are involved in plant growth and final yield, with varying contributions in accordance to shortage conditions and subsequent stress magnitude. For instance, nitrogen balance can be considered as a second order process under water shortage conditions whereas it is a first order one when there is no water stress (Brisson et al., 1998; Steduto et al., 2009). Accounting for these processes is paramount since they are driven by soil and weather conditions, in accordance to crop type and farming practices, whereas they can significantly influence several environmental processes. For instance, the crop type and related farming practices impact (i) the energy budget and thus, crop temperature warming or cooling via radiation storage (Doughty et al., 2011), (ii) the water budget and related crop water consumption or reservoir refill via infiltration and drainage (Pei et al., 2015; Mercau et al., 2016), (iii) the carbon budget and in-soil sequestration (Mathew et al., 2017), or (iv) the nitrogen budget and related aquifer contamination (Turkeltaub et al., 2015). Thus, the models simulating these processes can be used within integrated modelling schemes to diagnose current situations and prognosticate possible impacts for forthcoming management methods. They allow providing recommendations about farming practices at the agricultural field scale (e.g. nutrients, irrigation) in order to address agricultural concerns (e.g. yield, water use efficiency, salinity).

Crop models are designed to simulate the soil-crop functioning on a daily time step at the field scale, by including the above-mentioned processes along with weather conditions and farming practices (e.g. tillage, sowing, fertilization, irrigation, or harvest). Widely used models comprise the CERES model which is included in the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003; Shelia et al., 2019), the WOrld FOod Studies (WOFOST) model (Diepen et al., 1989), the Simulateur mulTIdisciplinaire pour les Cultures Standards (STICS) model (Brisson et al., 1998, 2003), or the DAISY model (Abrahamsen and Hansen, 2000; Salazar et al., 2017). These models were developed for different purposes and for different crop types, and they subsequently differ in the description and parameterization of the processes. For instance, DSSAT and STICS simulate water, nitrogen, energy and carbon budget, DAISY additionally addresses pesticides, whereas WOFOST focuses on carbon and water by disregarding nitrogen balance. Some agricultural applications may also require the description of the crop growth over large extents, and therefore running numerous simulations in a multi-local spatially distributed manner. This requires the development of parsimonious methods with reduced parameter numbers, such as AQUACROP (Steduto et al., 2009) and SAFYE (Duchemin et al., 2008) that address crop biomass production in relation to water availability (Silvestro et al., 2017; Han et al., 2019).

In order to overcome the temporal mismatch between crop model daily time scale and instantaneous remote sensing observations, especially when considering surface temperature that is highly variable throughout the day, an alternative was proposed by coupling crop and Soil-Vegetation-Atmosphere Transfer (SVAT) models (Olioso et al., 2005b). SVAT models simulate energy, water and CO_2 fluxes, and optionally nitrogen or volatile organic compounds (Garrigues et al., 2015). They differ from crop models by simulating fluxes at the sub-hourly scale rather than the daily scale, without considering the crop phenological status.

2.3.2. Data forcing and assimilation

Although dynamic crop models allow assessing secondary variables such as crop yield or water stress, they are limited by their assumptions and the difficulty to adequately set up various parameters and variables that drive the different processes. Therefore, it is mandatory to reduce the uncertainties on these parameters and variables to better simulate the actual crop growth. Among other sources of information such as *in situ* measurements or meteorological data, remote sensing can help in tuning these parameters and variables or in characterizing the crop type. In theory, the combination should be relatively straightforward since the models typically simulate state variables that can be retrieved from remote sensing: LAI and fAPAR, canopy cover, soil moisture, or surface temperature.

Model simulations can therefore be constrained by the remotely sensing variables to increase their accuracy. This can be achieved in three different ways (Bouman et al., 1997; Ines et al., 2013) (i) by forcing or updating a crop model output to be the one retrieved from remote sensing at each date of acquisition (Casa et al., 2012), (ii) by calibrating or recalibrating some model parameters based on past observations (Olioso et al., 1999, 2005a; Montes et al., 2014), and (iii) by data assimilation, *e.g.* by combining on-going simulations with newly acquired remote sensing retrievals to sequentially update the model parameter in near-real time. For more information on remote sensing data assimilation techniques, the reader is referred to the reviews performed by Dorigo et al. (2007) and Jin et al. (2018). It is worth noting that model calibration and sequential updating are complementary methods: prior calibration can be conducted on historical data to further conduct short-term or long-term simulations. Then, sequential updating can be used to refine near-future simulations and

control in near real-time state variables related to management (e.g. root-zone soil moisture and soil nitrogen content for optimizing fertilization and irrigation).

2.3.3. Methods exploiting contextual information

Methods based on contextual information make use of spatial or temporal contrasts captured by images collected over the solar and thermal spectral domains, mainly to evaluate the plant water status in relation to the evapotranspiration process (Kalma et al., 2008). First attempts used the temperature-vegetation index scatterplot such as the Water Deficit Index (WDI) (Moran et al., 1994) and the triangle method (Gillies et al., 1997), or the temperature-albedo scatterplot such as the Surface Energy Balance Index (SEBI) (Menenti and Choudhury, 1993; Roerink et al., 2000). In both cases, the idea is to estimate a water status proxy (e.g. water deficit index or evaporative fraction) from the distance, within the scatterplots, to the extreme temperature values corresponding to the extreme water status (e.g. fully wet or fully dry). These extreme temperature values are determined either from the contrast captured within the thermal images (Gillies et al., 1997; Roerink et al., 2000), or from the energy balance inversion along with local micro-meteorological measurements (Menenti and Choudhury, 1993; Moran et al., 1994). A similar approach is proposed by Su (2002) with the Surface Energy Balance System (SEBS) that estimates evaporative fraction from energy flux values under extreme conditions along with observations under current situations. Further investigations deepened the analysis of the temperature-vegetation index scatterplot by defining soil moisture isolines with the Temperature Vegetation Dryness Index (TVDI) (Sandholt et al., 2002; Zhu et al., 2017). Finally, Bastiaanssen et al. (1998) proposed a more elaborated way to make use of spatial contrasts with the Surface Energy BALance algorithm for land (SEBAL) model, by solving surface energy balance over wet and dry areas to calibrate a linear relationship between surface and air temperature. Overall, these approaches have provided acceptable estimates for evapotranspiration, either instantaneous or at the daily time scale (Jacob et al., 2002; French et al., 2005; Gómez et al., 2005; Galleguillos et al., 2011a, 2011b; Chirouze et al., 2014; Kamali and Nazari, 2018; Ma et al., 2018). Recent developments on the use of contextual information related to evapotranspiration consists in finding links between the temperature-vegetation index and the temperature-albedo scatterplots. The idea is to better constrain the inversion of the energy balance under specific conditions such as wet and dry soil, or green and senescent vegetation (Merlin, 2013; Merlin et al., 2014).

2.4. Spatiotemporal matching: gap-filling and disaggregation techniques

Using remote sensing data for agriculture monitoring faces several spatial and temporal constraints. For instance, adapting farming practices for sustainable development requires at least a decametric spatial resolution while yield monitoring for food security objectives can be performed at larger scale (e.g. hectometric, kilometric). In the same way, nitrogen fertilization is performed at specific growth stages, which makes the availability of remote sensing data near the corresponding dates mandatory to obtain reliable model predictions. It is often not possible to satisfy directly such requirements due to technical constraints such as revisit frequency and cloud occurrence for solar and thermal infrared domains, which results in incomplete time series both in space and time. Furthermore, time series may often show unexpected behavior due to noise in the data and especially sharp variations due to cloud mis-detection when considering satellite data.

The problem of smoothing and temporal gap-filling is not specific to agricultural applications and has been widely addressed in the remote sensing community. There is an abundant literature in this domain (Gao et al., 2008; Chen et al., 2011; Delogu et al., 2012; Kandasamy et al., 2013; Moreno et al., 2014). Temporal gap filling is thus a way to provide the remote sensing information in a timeliness that is compatible with the crop growth time. Another approach consists in disaggregating data acquired with an appropriate temporal sampling but with a too coarse spatial resolution for the considered agricultural application data. The disaggregation is achieved by combining these coarse spatial resolution data with finer resolution imagery to provide data at high spatial resolution and high revisit frequency (Agam et al., 2007; Roy et al., 2008; Merlin et al., 2012; Ha et al., 2013; Li et al., 2017).

3. Remote sensing applications in agriculture

Agricultural stakeholders (e.g. farmers, agricultural cooperatives, local, national or international authorities) have to meet multiple goals: conducting activities that are economically viable, ensuring agricultural productions to feed a growing population, and reducing or even reversing the negative environmental impacts by minimizing the resource depletion and contributing to climate mitigation. As remote sensing is a nondestructive way of spatially and temporally monitoring vegetation, it appears as an inevitable tool to help achieving these goals. It can contribute to the identification of new varieties that better fit challenging contexts (e.g. phenotyping), to the monitoring of agricultural land use, to the forecasting of within-season crop production, to the optimization of short-term production, and to the provision of ecosystem services related to soil or water resources as well as to animal or plant biodiversity. These different applications are related to various stakeholder requirements that involve different spatial scales (e.g. local, regional, or global) and different temporal scales from real time to decades, with various levels of accuracy, and a priori knowledge on crop status (Table 2). This directly affects the choices of remote sensing based solutions in terms of data acquisition (e.g. proximal sensing, UAV, satellite, sensor) and methods (e.g. empirically or physically based). In this section, we address recent research developments that permit to strengthen applicative capabilities in remote sensing for the aforementioned thematics, in complement to the review from Atzberger

Table 2
Applications of remote sensing in agriculture for the different stakeholders and corresponding spatial and temporal scale requirements. RT stands for Real Time, CC is Crop Cycle, Y is year and LTDA corresponds to Long Term Data Archive.

Applications in agriculture	Farmers		Local authorities	Private sector Agribusiness	Governments	International Organizations
	Field	Farm	Management area[a]	Distributed Fields[b]	Country	Global
Phenotyping				RT		
Land use monitoring			CC, Y, LTDA	CC, Y	Y, LTDA	Y, LTDA
Yield forecasting	RT,CC	RT,CC	Y	RT, CC, Y, LTDA	Y, LTDA	Y, LTDA
Precision Farming	RT	RT		RT, CC		
Ecosystem Services		CC, Y, LTDA	CC, Y LTDA		CC, Y, LTDA	CC, Y, LTDA

[a] Management Area: multi-actors within a regional area, with convergent or divergent interests.
[b] Distributed Fields: in case of phenotyping activities, this concerns micro-plots planted with different genotypes and grown in different conditions (e.g. nitrogen, water), in case of faming cooperative or industry, the fields may be distributed over regions that may be located within a single or several countries.

(2013) which was limited to operational monitoring systems at large scale.

3.1. Breeding/phenotyping

Selecting the best cultivars to improve the crop production has been practiced for thousands of years by farmers. Plant varieties are indeed adopted by the farmers because they improve yield, they are more resistant to specific diseases or pest infestation, and they are adapted to a given environment characterized by an ensemble of conditions including climate, soil, and farmer practices. For their selection, crop breeders must therefore cross a maximum of phenotypic and genomic information in given environmental conditions by quantitatively measuring the plant anatomical, ontogenetical, physiological, and biochemical properties (Walter et al., 2015).

Phenotyping experiments were first conducted in controlled conditions with plants in pots in greenhouses or gas chambers. However, several studies have shown some limitations of these experiments such as the reduced soil volume or depth or the plant microclimate that do not reproduce actual field conditions (Mittler and Blumwald, 2010; Fiorani and Schurr, 2013; Araus and Cairns, 2014). Conversely, high-throughput field phenotyping allows to characterize genotypes of a given species within given environmental requisites and agricultural practices, by monitoring thousands of plots composed of varieties sowed along few rows.

While the genotyping efficiency increased significantly this past 30 years thanks to DNA sequencing, the field phenotyping capabilities progressed more slowly due to the need for developing means to carry out repeated measurements over a huge number of plots throughout the crop cycle (White et al., 2012). Nondestructive and automatic measurements are indeed mandatory to monitor a phenotyping platform, making proximal and UAV remote sensing essential for these experiments. This requires the design of robots that automatically acquire the data (Deery et al., 2014), the design of sensors mounted on these robots (Li et al., 2014), and new methods to process, analyze, and interpret the data (Kamilaris and Prenafeta-Boldú, 2018). Finally, the high throughput nature of field phenotyping raises the questions of data storage and computing facilities (White et al., 2012). If precision farming allowed making progress in understanding and exploiting the signal at the canopy level to detect intra-field heterogeneities, high-throughput field phenotyping opens new ways to investigate remote sensing issues at the plant, and even at the vegetation element scale.

Considering the variety of available sensors, images of different nature (e.g. wavelength domain, spatial resolution) can be simultaneously acquired over the same plant or group of plants, raising the questions of optimizing the acquisition conditions (e.g. illumination, geometry, and footprint) and the sensors calibration (Del Pozo et al., 2014), as well as fusing the information content of the different wavelength domains (Virlet et al., 2017). Most of the phenotyping studies consider both passive RGB (Red Green Blue) and/or multispectral images, sometimes combined with active LIDAR or sonar sensor. However, other sensing techniques have potential interest, such as fluorescence in relation to chlorophyll and nitrogen content that is today limited to handheld sensors due to technological issues (Tremblay et al., 2012). The thermal infrared spectral domain is also underexploited since the signal is much more variable in time according to the plant stand microclimate (Munns et al., 2010; Andrade-Sanchez et al., 2013; Walter et al., 2015). Furthermore, the calibration of Thermal InfraRed (TIR) sensor in field conditions is also more complex and delicate as compared to the solar spectral domain (Gómez-Candón et al., 2016).

Up to now, RGB images are mainly exploited for classification or segmentation purposes (e.g. for plant and organ counting, or the identification of diseases or pest infestations) while the multispectral images are used to assess architectural traits (mostly green area index) or leaf biochemical content (e.g. chlorophyll, water, nitrogen) through radiative transfer model inversion. LIDAR acquisitions, stereo RGB images, and sonar are mainly exploited to provide canopy height (Andrade-Sanchez et al., 2013; Holman et al., 2016; Madec et al., 2017), while much more information is expected from the generated 3D point clouds to describe the plant stand architecture, including the area, the density, and the orientation of the different plant parts (e.g. leaf, stem, ear, or flower). Root zones measurements were little investigated in field phenotyping experiments due to obvious limitation of underground sensing. However, few attempts were made using camera or scanner technologies in clear rhizotron tubes to characterize the root architecture or using electrical resistivity tomography by linking the measured signal to the root water absorbance rates (Zhu et al., 2011; George et al., 2014; Postic et al., 2019).

Up to now, the information content of images acquired in phenotyping experiments appears underexploited as compared to satellite remote sensing. For example, most of the phenotyping studies dealing with multispectral cameras establish statistical relationships or use machine learning algorithm to relate vegetation indices and traits such as leaf area index, or chlorophyll and nitrogen content (Araus and Cairns, 2014). Few of them investigated the use of radiative transfer models to simulate the leaf or plant stand radiative behavior. Thorp et al. (2015) and Jay et al. (2017) showed that the statistical and model inversion approaches are performing similarly in the phenotyping context, providing that the dataset used to calibrate the statistical relationships is large enough to well represent the range of possibilities, including new cultivars. However, these results are limited by the use of a 1D generic radiative transfer model that may not be adapted to describe the crops at the considered spatial resolutions (especially for row crops). More developments in 3D modelling and inversion are thus required to develop operational pipelines over given species. This can be supported by field phenotyping experiments that allows detailed description of crop architecture thanks to 3D point clouds generated by Structure from Motion (SfM) or LIDAR techniques (Liu et al., 2017).

Images of different natures were most of the time used independently to assess distinct traits. However, recent studies combined traits derived from different spectral domains to assess more complex traits, mainly by establishing statistical relationships between them. For example, Tilly et al. (2015) and Bendig et al. (2015) used the canopy height from LIDAR or SfM algorithm applied on RGB image and vegetation indices to assess the above ground biomass. Another way of exploiting the complementarity between the sensors was explored by Jay et al. (2018) who used the vegetation green fraction estimated from machine learning applied on RGB images at high spatial resolution (6 mm) to optimize the threshold value applied to the vegetation index computed over the multispectral image of lower spatial resolution (between 1 cm and 3 cm), with the objective of separating the green pixels from the background and then correct the estimation bias from the multispectral image. However, the synergy between sensors could go further, for instance, plant height estimated from LIDAR or stereo images, and cover fraction estimated from RGB images could also be combined together with TIR images to better assess the water balance of the plant stand.

The high throughput nature of field phenotyping allows gathering training datasets compatible with the development of deep learning techniques (Pound et al., 2017). Huge progress has been recently achieved in image classification, segmentation, and object identification in plant stands thanks to high throughput phenotyping experiments (Singh et al., 2016). However, these techniques are supervised and require image annotation to identify the different classes, which necessitates expert knowledge and remains tedious and time consuming (Kamilaris and Prenafeta-Boldú, 2018). Like any supervised classification method, they are sensitive to the composition of the learning dataset and as such, are dependent on the crop type, sensor spatial and spectral resolution, and the condition of acquisitions (Mohanty et al., 2016). They are thus still barely transposable from one species to another or from one phenotyping platform to another (Kamilaris and

Prenafeta-Boldú, 2018).

3.2. Agricultural land use monitoring

One of the most straightforward uses of remote sensing for agricultural purposes is to make maps of the agro-ecological landscape. It may be useful to recall the distinction between land cover, which relates to the physical properties of a land surface, and land use, which corresponds to the activities or functions for which humans utilize the land (Lambin et al., 2006). These notions are conceptually distinct, yet inherently related, and both are useful in an agricultural context. Mapping the agro-ecological landscape is achieved by applying classification algorithms resulting in discrete categories on spatialized remote sensing measurements. By repeating this procedure over time, one obtains the capacity to monitor changes. While global mapping efforts based on remote sensing exist (see Gómez et al. (2016) for a review), they generally do not satisfy the needs of agricultural applications. Indeed, the dynamic nature of agro-ecosystems in space makes the task particularly complex: it is easier to map distinct land cover types, such as forests and grasslands, than the various types of crops within cropping systems. Global mapping efforts based on remote sensing, such as ESA-CCI Land Cover (Bontemps et al., 2013) or Globeland30 (Chen et al., 2017), typically focus only on land cover, and they clump most agricultural lands in a single 'cropland' class, which is of limited use for most agricultural stakeholders, apart from those seeking rough large scale statistics of changes in cropland area. Therefore, there are dedicated efforts to specifically map crops by harmonizing and fusing existing maps at different spatial resolutions to provide crop layers (Fritz et al., 2015; Waldner et al., 2016). However, higher interest relies in mapping and monitoring aspects that are related to how the land is used and modified by farmers, and more specifically mapping crop practices. For a deeper analysis, the reader is referred to the review of Bégué et al. (2018) which details the mapping of different crop successions (e.g. crop rotation and fallowing) of cropping patterns (e.g. single tree crop planting pattern, sequential cropping, and intercropping/agroforestry), and of cropping techniques (e.g. irrigation, soil tillage, harvest and post-harvest practices, crop varieties, and agro-ecological infrastructures).

The main stakeholders seeking for land use monitoring information are regional to national and international agents (e.g. land planers and policy makers), but generally not individual farmers. Indeed, farmers actually know better which crop variety they have sown and how they manage their farms than what is provided by current remote sensing capabilities, although exceptions might include farming companies, which remotely manage larger, or multiple estates. At regional and global levels, crop specific masks are required to identify zones of interest for yield forecasting purposes (see section 3.3), they can also be used as a source for general statistics on acreage, or for insurance markets (de Leeuw et al., 2014).

The large bottleneck for precise land use monitoring with remote sensing has been the lack of sufficiently fine spatial resolution data with an adequate revisit frequency, and enough spectral information, along with the capacity to process it efficiently. Indeed, the spatial resolution must be in agreement with the crop field size, especially when considering smallholders farms. For example, in Africa, 25% of fields are less than 0.5 acres (Burke and Lobell, 2017). Higher revisit frequency is needed to avoid clouds, to ensure a large geographical coverage and to finely detect changes, such as those expected from managing practices (e.g. harvesting or mowing for instance) or from adverse weather events (e.g. lodging in cereals). A better spectral sampling should also allow identifying crop types and varieties, and the advent of constellations such as Sentinel-2 are providing unprecedented capacity to do this (Defourny et al., 2018). Furthermore, fusing remote sensing data from different sources (e.g. optical and SAR) generally perform better for cropland mapping than single sources (Joshi et al., 2016). Timeliness is also crucial since early season crop mapping is also of high interest for crop production forecasting in the food security context (Skakun et al., 2017). Finally, the arrival of cloud computing for remote sensing (Gorelick et al., 2017) facilitated the exploitation of both Sentinel-2 spectral information and remote sensing data from different sources. Such emerging technology allows for a paradigm shift towards dedicated crop type mapping over large geographic extents (Azzari et al., 2017), which can leverage on new techniques like adjusting the spatial resolution requirements locally (Waldner et al., 2018). However, the accuracy of crop maps still depends on the performances of the classification methods used to generate them. The composition of the training dataset in such supervised algorithms remains an issue, especially in southern countries where the agricultural landscape is highly heterogeneous and very scarce data are available (Xiong et al., 2017).

Remote sensing will have an increasingly important role for monitoring agricultural land use as the agro-ecosystems change their spatial configurations under the pressure of various drivers. Such drivers include climate change, which is expected to modify the spatial patterns of crop suitability (Ramankutty et al., 2002), and therefore to induce changes in crop type within numerous regions. Additionally, changes in farming practices, such as adopting regenerative agriculture approaches that prone zero-tillage and crop diversification in order to restore soils, will also modify the spatial organizations of farming systems. Overall, policy-makers and local to regional decision makers will increasingly need updated spatial information of how agro-ecosystems evolve in order to improve their management.

3.3. Crop yield forecasting

Anticipating how productive a crop will be ahead of harvest is of direct interest to various stakeholders: individual farmers to optimize the production quality and quantity, national governments and international institutions to strengthen food security, especially in developing countries, and private companies such as crop insurers or commodity traders (Filippi et al., 2019; Kogan, 2019; Kogan et al., 2019). The typical indicator of productivity that is considered in this context is crop yield, *i.e.* the ratio of the total mass of harvested product (such as grain) to the area used to grow the crop. The spatial scale at which this information is of interest depends on the stakeholder. Farmers would focus at the field or farm scale, interested in anticipating their potential financial returns from their own fields. Governments, commodity traders, and international organizations are rather interested by yield estimates aggregated at coarser scales, such as individual administrative units or regional and national level. Such information is relevant for policy-makers to inform decisions on trade, market intervention or humanitarian assistance. Crop insurers are interested in both fine and coarse scale in order to assess the potential crop yield losses of individual fields, but also to compare these to the regional context at a coarser scale. This section focuses on crop yield forecasting over large geographic extents, while the field scale, where ancillary information is generally more abundant is addressed in section 3.4.

Global and regional scale agricultural monitoring systems currently exist with the objective to provide up-to-date information on food production. For a detailed analysis of such systems, we refer to the recent dedicated reviews by Fritz et al. (2019) and Atzberger (2013). All of these systems rely partly on remote sensing, as a source of indicators of crop status in near-real time that can be related to crop yield, with the specific advantage of providing spatially and temporally explicit descriptions of the heterogeneity of agricultural landscapes (Lobell, 2013). The role of remote sensing in this context has further been strengthened by the GEOGLAM initiative, launched by the Group on Earth Observations (GEO) and endorsed by the G20, with the objective of exploiting Earth Observation (EO) data to provide timely and accurate forecasts of agricultural production at national, regional, and global scales (Becker-Reshef et al., 2010a).

The more straightforward approach to link remote sensing to yield is to establish empirical relationships between *in situ* yield statistics and

the remotely sensed indicators. Simple methods rely on using the NDVI (Normalized Difference Vegetation Index) peak from coarse spatial resolution (0.05°, approximately 5.5 km) time series (Becker-Reshef et al., 2010b), which can further be anticipated by using an expression of time based on cumulated temperature sums (Franch et al., 2015). Other studies have focused on other indices, including phenological metrics extracted from vegetation indices time series to improve yield estimation (Bolton and Friedl, 2013; Sakamoto et al., 2014). Very few studies focused on yield quality (Moriondo et al., 2007; Wang et al., 2014), which is more difficult to assess since it is highly dependent on genotypes (Magney et al., 2016). However, these studies typically target the simpler cases of relatively homogeneous landscapes as found in the US and China. In other parts of the world, agricultural landscapes are more heterogeneous with a higher diversity in crop types, crop management practices, and thus field sizes (Duveiller and Defourny, 2010). Indeed, López-Lozano et al. (2015) showed that the correlations between the cumulated fAPAR and yields in Europe vary widely depending on the crop type and geographic locations, especially in Northern Europe where the inter-annual yield variability is too low to be easily detected from remote sensing data in the solar spectral domain. The problem of small field sizes is exacerbated in smallholder landscapes, which are often more likely threatened by food insecurity. The small size of the fields also implies a lack of reliable yield statistics to establish robust empirical relationships. Furthermore, such landscapes are often located in intertropical regions where estimating yield from remote sensing observations is complicated by an abundant cloud coverage during the growing season, making the use of optical remote sensing more challenging (John et al., 2015; Whitcraft et al., 2015). These various challenges are part of the reason why global operational monitoring systems currently use remote sensing mostly to assess crop condition in a qualitative manner by computing anomalies (e.g. the ASAP system, see Rembold et al. (2019)) which are then investigated by analysts to infer their effects on yield (Fritz et al., 2019).

In theory, any empirical relationship that links yield to satellite observations could be replaced by dynamically assimilating remote sensing products (e.g. data or primary variables) into a mechanistic crop growth model to result in a near real-time forecast, perhaps even to simulate the future of the crop growth based on seasonal weather forecasts (see section 2.3.2). Although the idea of assimilating satellite data into models to improve regional and global yield forecasting has been around for a long time (Delécolle et al., 1992; Moulin et al., 1998; Doraiswamy et al., 2005; Dorigo et al., 2007), in practice, this approach is still mostly used in research rather than in operational applications. Furthermore, while it has been used to some extent over fragmented landscapes with large crop diversity (Dente et al., 2008; de Wit et al., 2012), most studies focus on simpler homogeneous landscapes such as the US and China (Ines et al., 2013; Xie et al., 2017). Up to now, the main limitations were technical and remained in combining fine spatial resolution, high temporal revisit frequency, and large geographic coverage. To alleviate this problem for yield monitoring, some solutions have been proposed, such as selecting subsets of purer time series by using innovative techniques based on sensor information (Duveiller et al., 2011a, 2015) or using disaggregating techniques to fuse infrequent high spatial resolution imagery with high revisit but coarser data (Gao et al., 2008; Zurita-Milla et al., 2009; Franch et al., 2019). These techniques will retain value to exploit the past data archive, but current and future methods should rather evolve towards the synergistic use of the free high spatial resolution imagery (Sentinel 1 and 2, Landsat, Gaofen, etc.) facilitated by an easy access to data and cloud-computing platforms. An example includes Lobell et al. (2015), who took a similar approach as described in section 2.2.2 (e.g. machine learning for radiative transfer model inversion). They calibrated empirical relationships between LAI time courses and corresponding yields simulated with a crop growth model. These empirical relationships were then applied to satellite information along with weather metrics to predict yield at field scale, leveraging on the recent capacity to use voluminous Landsat imagery within a cloud-based platform. Such approach was recently evaluated in US and developing countries with comparable performances, but without requiring heavy calibration based on past yield statistics (Azzari et al., 2017).

This increased accessibility to more appropriate data (in terms of spatial and temporal resolution) and the development of machine learning techniques should open the road to finally achieve operational data assimilation of remote sensing data into dynamic crop models, much like what is done in weather forecasting. Furthermore, the combined use of more sources of complementary satellite information, whether with empirical relationships or within mechanistic models, is bound to provide enhanced explanatory power to infer crop yield.

3.4. Monitoring crops for yield optimization: precision farming

The use of remote sensing in precision farming applications started in the 1980's and is now operationally used all around the world (Moran et al., 1997; Mulla, 2013). It is one of the principal means able to provide spatial and temporal information on the crop status in a nondestructive way for a sustainable crop management. Furthermore, in the past ten years, huge technological advancement was achieved in the design of both dedicated proximal and remote sensing platforms (e.g. Internet Of Things IOT, UAV, UGV) and vehicles equipped with variable rate application technologies. At the satellite level, the availability of free Sentinel-2 images allows fulfilling both the spatial (e.g. metric to decametric) and temporal requirements (e.g. revisit time of five days) for crop growth monitoring at the farm level. This technical progress now makes precision farming affordable and cost-effective and thus, almost operational. Most of existing studies relied on the use of data collected over the solar domain (e.g. multispectral reflectance and fluorescence data), and the thermal infrared domain. Although hyperspectral remote sensing has been demonstrated useful in many precision farming applications (Inoue et al., 2012; Mariotto et al., 2013), this technology remains too expensive to be used in an operational context.

Remote sensing for precision farming covers a large range of applications that include weed (Lamb and Brown, 2001; Thorp and Tian, 2004; Lopez-Granados, 2010) and disease (Mahlein et al., 2012; Mahlein, 2015) detection, nutrient (Baret et al., 2007), and water stress (Calera et al., 2017) monitoring in relation with yield optimization, or the characterization of soil properties (Ge et al., 2011) (e.g. organic matter, clay content or salinity). Concerning weed detection, most of the studies mainly dealt with detecting weeds between rows, which means detecting the rows and then the vegetation in between them, based on the geometric structure of the rows and the spectral contrast between vegetation and soil. However, the problem becomes harder when weeds and crops are mixed together within the same image (Lamb and Brown, 2001) and have a similar spectral behavior. More information (e.g plant shape or at least spatial pattern) is then needed and requires the use of OBIA (Pérez-Ortiz et al., 2016) or deep learning (Hung et al., 2014) techniques. However, the main limitation relies in the spatial resolution that must be lower than the crop/weed size or pattern (Lopez-Granados, 2010), which is only possible with UAV/UGV or proximal sensing. Timing is also crucial to allow a rapid farmer action so that the crop growth is not affected by the presence of the weeds. The same applies to the detection of plant diseases that mainly relies on the difference in spectral behavior between the infected and the healthy plants, (Bravo et al., 2003; Mahlein, 2015).

When considering nutrient (mainly nitrogen) and water stress, the use of remote sensing data solely is not sufficient to assess the actual need since plant nitrogen and water requirements are secondary variables. It is necessary to have supplementary information to describe the crop system and this is generally achieved in two ways: either by using statistical approaches or by assimilating remote sensing data into land surface models (e.g. crop functioning, SVAT). In operational context, data assimilation systems are still not used due to their low flexibility and complexity. Therefore, most of the systems rely on simple

relationships between indices and the variable of interest: nitrogen (Clevers and Gitelson, 2013; Diacono et al., 2013; Jin et al., 2017), yield quality (Li et al., 2015; Barmeier et al., 2017), water stress (Bellvert et al., 2014), crop coefficient (Glenn et al., 2011; Campos et al., 2018) or irrigation needs (Calera et al., 2017). Some of them also make use of other local measurements, including the use of *in situ* wireless sensors (Tokekar et al., 2016) to better constraint the variable retrieval (Eitel et al., 2014). While the spatial resolution is not a constraint anymore thanks to the availability of decametric satellite sensors over the solar spectral domain, the timing capabilities (e.g, revisit frequency combined with cloud occurrence) is crucial, and the use of complementary UAV or proximal sensing is still required for such applications. The acquisition time is even more critical when considering thermal infrared acquisition in relation to plant water status because of the high variability of the temperature within the canopy and throughout the day.

Remote sensing from any platform (e.g. proximal, UAV or satellite) has been applied successfully and shows a great potential for precision agriculture in a context of rapid technological development. However, practical considerations must remain in mind. The system must be cost-effective and the farmer must be equipped with a consistent technology to adapt crop management practices (Hunt and Daughtry, 2018). Furthermore, a good compromise must be found between the level of complexity, the decision tool accuracy, and the farmer capacities to use it (Seelan et al., 2003). Therefore, significant efforts must be achieved to train the end-users of support decision tools (Mondal and Basu, 2009).

3.5. Agriculture for ecosystem services

Beyond production of food and biofuels, other functionalities of agriculture include water preservation (e.g refill of underlying aquifers or downstream dams, decrease in water withdrawals into aquifers, rivers or ponds), soil preservation (e.g. erosion mitigation, maintaining of soil fertility), carbon sequestration, and biodiversity conservation. These functionalities are converted into ecosystems services based on quantitative assessment, either economical or societal, which is a delicate task since socio-economical valuation can vary depending upon stakeholder-oriented services (de Groot et al., 2002; Hein et al., 2006). Agricultural activities involve field scale actions such as intercropping, crop rotations, and management practices (e.g. tillage, irrigation, fertilization, chemical treatments, pruning, harvest, and residues). Besides, the landscape infrastructure is also impacted by agricultural activities in relation to spatial planning, such as land use or networks of hedgerows, benches, ditches, and ponds (Swinton et al., 2007). These anthropogenic drivers induce various biotic and abiotic impacts in the surrounding landscape compartments and the Earth system. For instance, transports of soil matter, pesticides, pathogens, seeds, pollen, vegetation species or animals are driven by hydrological (e.g. drainage towards underlying aquifers, runoff towards downstream areas), micrometeorological (e.g. heat and gas exchanges between soil or vegetation and boundary layer), or atmospheric (e.g. wind-based transports) fluxes (Gil et al., 2007; Chamecki et al., 2009; Danesh-Yazdi et al., 2016; Wanyama et al., 2018). The landscape partitioning resulting from the management practices impacts the storage, buffering, and hosting capabilities (Nagendra et al., 2013; Mairota et al., 2015; Dollinger et al., 2016). In this context, some remote sensing products have been identified as Essential Biodiversity Variables (EBV (Pettorelli et al., 2016),) and are used in various frameworks dedicated to diagnose current situations and prognosticate forthcoming ones (Simons et al., 2017).

Diagnostic approaches rely on real-time indicators directly derived from remote sensing data by using digital terrain attributes such as elevation, spectral indices, or prescribed values based on statistical approaches (Osborne et al., 2001; Bradbury et al., 2005; de Araujo Barbosa et al., 2015; Winowiecki et al., 2016; Braun et al., 2018). Based on these indicators, remote sensing offers capabilities for continuous monitoring in a spatially distributed manner, where GIS (Geographic Information System) based frameworks allow the implementation of long-term observatories thanks to the combination of satellite and field data to compute a variety of metrics (Fegraus et al., 2012). The mapping and revisit capabilities offered by remote sensing also permit to quantify the spatiotemporal variation in ecosystem services according to land use and landscape fragmentation (de Araujo Barbosa et al., 2015) with some focus on soil carbon storage and soil erosion conservation (Winowiecki et al., 2016; Pineux et al., 2017; Braun et al., 2018).

Prognostic approaches rely on quantifying functionalities for prospective scenarios, where functionalities are derived from integrated modelling frameworks or geomorphological attributes (Marshall and Randhir, 2008; Fahrig et al., 2011; Shi et al., 2012; Erol and Randhir, 2013; Nagendra et al., 2013; Schilling et al., 2014; Qiu and Turner, 2015; Levavasseur et al., 2016). These functionalities include evapotranspiration loss, water use efficiency, runoff reduction, groundwater recharge, flood controls, soil loss, water quality with nitrogen and phosphorus reduction, as well as animal hosting. Remote sensing data are used for documenting permanent structures such as topography and soil properties, as well as calibrating and validating the modelling tools. In this last case, remotely-sensed products of interest (e.g. leaf area index, evapotranspiration) are combined with field data such as nested runoff measurements for multi-objective and multi-criteria calibration procedures (Romaguera et al., 2010; Rientjes et al., 2013; Carvalho-Santos et al., 2016; Ha et al., 2018; Ma et al., 2019).

The use of remote sensing data as additional information to help understanding ecosystems, in particular in relation to agricultural activities is now established. However, more efforts must be put to translate functionalities into ecosystem services thanks to socio-economical valuations (Polasky et al., 2015), as well as to strengthen systemic analysis with trade-offs between ecosystem services via participatory approaches (van Oort et al., 2015; Braun et al., 2018). When dealing with biodiversity conservation, the challenges are even higher since efforts have to be conducted for defining indicators based on existing past remote sensing data (Rose et al., 2015; Skidmore and Pettorelli, 2015). Furthermore, the reliable assessment of ecosystem services highly depends upon (i) accurate land cover assessment, since land cover strongly drives the spatial distribution of ecosystem functionalities subsequent uses (de Araujo Barbosa et al., 2015), and (ii) accurate characterization of functionalities via radiative transfer models and land surface process models (Andrew et al., 2014). Finally, a forthcoming challenge beyond the remote sensing community, and that results from the issues discussed above, is the necessity to build bridges between the involved communities so that any mean is helpful beyond the related discipline (Rose et al., 2015).

3.6. Remote sensing for agriculture: caveats and ways forward

While the feasibility of employing remote sensing techniques in the field of agriculture has been demonstrated since the 1980's, the operational use of remote-sensed data has been recently intensified and operationally used for a variety of agricultural applications (Defourny et al., 2019). Indeed, the last decade was characterized by a sharp increase of technological developments in the acquisition systems (e.g. GAOFEN-1, SENTINEL-2 launches for Earth Observation data, democratization of UAV and robot platforms, Internet Of Things - IOT (Ojha et al., 2015)), as well as in the data storage, computing facilities, and algorithm such as deep learning techniques for data processing. Moreover, these technological improvements are becoming affordable for most of the users, making the exploitation of remote sensing reliable and profitable (Wolfert et al., 2017).

Considering satellite platforms, developments are still in progress to develop new sensors that can provide richer spectral and directional information and are compatible with the requirements of agricultural applications (e.g. revisit frequency should be lower than a week, and

spatial resolution should at least be decametric). While the optical domain is already considerably exploited, investigation on thermal infrared missions for water resources management (Hulley et al., 2017; Lagouarde et al., 2018) as well as hyperspectral missions for vegetation (Guanter et al., 2015) or soil degradation monitoring (Carrere et al., 2013) are currently running. New types of data sources are also becoming increasingly available and are being tested for agricultural applications. An example is yield estimation using L-band vegetation optical depth (Chaparro et al., 2018) or sun-induced fluorescence (SIF) (Guan et al., 2016; Song et al., 2018). SIF reserves quite some promise, as the signal is directly related to the photosynthetic capacity of the canopy (Porcar-Castell et al., 2014). While it has been available at very coarse spatial resolution for some years (e.g. since 2007 from GOME-2 at 40 km spatial resolution), new possibilities to monitor vegetation stress and gross primary production are emerging with the TROPOMI mission (7 km spatial resolution) on-board of Sentinel 5P (Veefkind et al., 2012; Köhler et al., 2018), and with the dedicated space explorer mission FLEX at 300 m resolution (FLuorescence EXperiment) mission (Drusch et al., 2017). However, these missions are still only compatible with large scale applications such as vegetation monitoring and yield forecasting at regional or global scale and may require additional downscaling techniques to reach the appropriate scale for agricultural applications (Duveiller and Cescatti, 2016).

Compared to satellite data, UAV platforms appear more flexible especially in terms of revisit frequency. Nevertheless, the use of such platforms is highly constrained by meteorological conditions (e.g., requirements about low wind speed and lack of precipitation), by existing regulations, by the spatial coverage that can be reduced by the autonomy or the battery or the maximum payload that limits the simultaneous use of different sensors. Furthermore, while inflight and vicarious calibration procedures are well characterized for satellite platforms (Dinguirard and Slater, 1999; Barsi et al., 2014), no standard procedure is available for inflight calibration of UAV-borne sensors. Indeed, the latter acquire images over calibration targets at specific times during the flight (Herrero-Huerta et al., 2014), while the key environmental conditions (e.g., illumination in the optical domain, temperature in the thermal infrared domain) may significantly vary throughout the flight, because of environmental factors (e.g. cloud shadows, wind regime, solar course). This can make the calibration fail and induce a lack of accurate signal quantification (Weiss et al., 2017; Wang et al., 2019). Finally, proximal sensing generally permits a good data accuracy, but it is limited by cost (e.g. internet Of Things) or manpower and is thus restricted to a low spatial and temporal coverage.

Regarding algorithms and methods, the remote sensing community now faces the era of big data, where machine and deep learning algorithms are increasingly growing with three main applications (Lary et al., 2016): (i) solving classification problems (Heung et al., 2016; Mohanty et al., 2016; Shelestov et al., 2017), (ii) developing model emulators, *e.g.* training machine learning techniques on a restricted amount of simulations to accelerate 3D physically based models that are computationally expensive (Gómez-Dans et al., 2016; Yuzugullu et al., 2017), by either considering radiative transfer models or some combination between RTM and crop functioning models, and (iii) building complex empirical relationships to retrieve crop variables from remote sensing data (Ali et al., 2015; Verrelst et al., 2018). However, these methods remain underexploited up to now: for example, machine learning has been mainly exploited to estimate variables at the pixel and instantaneous level, while these methods have the potential to account for the contextual information in space (Reichstein et al., 2019) and time based on historical series. Indeed, the use of past data helps improving short or near real time predictions, which is crucial, especially for crop management and yield forecasting (Verger et al., 2014a). The same applies for applications based on classification and segmentation where deep learning is still underexploited to consider both the spatial (e.g. field) and historical data (e.g. crop rotation) (Kussul et al., 2017). Machine learning is also an efficient way to mix data of different nature, including remote sensing sources but additional data could also be used such as *in situ* (farming management practices from field surveys, soil conditions) or climate variables (Debolini et al., 2015). Despite their efficiency and power, machine and deep learning approaches are constrained by the constitution of the training database, which should represent the spatial and temporal variability of the target and observation conditions, including the noise and biases associated with the data to preserve the generalization of the applicability of the method.

The proven efficiency of machine learning algorithms questions the relevance of using and developing mechanistic models to describe the physical, biological and agronomic processes (Baker et al., 2018). Indeed, although these latter are capable of describing the relation of causality between inputs and outputs, they correspond to oversimplifications of the reality and cannot render the full complexity of the relationship. Conversely, machine learning algorithms allow building relationships between any kind of data, by focusing solely on prediction capabilities while ignoring the underlying causalities. Their performances are thus related to the similarity between the current situation and those that constitute the training database. This limits their extrapolation capacities to predict specific or unanticipated behaviors and the question of how to qualify the representativeness of the training data set is still open. Conversely, the domain of validity of mechanistic models, even in unexpected conditions, is better controlled since the underlying assumptions and relationships between variables and co-variables are better known. Overall, the two approaches are complementary, and mechanistic models could be used to provide physical constraints and domain knowledge to machine learning algorithms (Reichstein et al., 2019).

The use of remote sensing data for agricultural applications raises a persisting issue: the gap between radiative transfer and crop functioning or process models. Although remote sensing data assimilation techniques have been developed in the past 20 years, the connection between the two kinds of models is still established through a limited number of variables (usually one or two). Furthermore, although remote sensing products are directly used in crop functioning models, the definition of the biophysical product that describes the radiative transfer is actually different from the agronomic variable that is used or simulated by the crop model. One of the best example is the leaf area index, defined as half the total green leaf area projected on a horizontal plane in crop functioning models while it corresponds most of the time to the total green intercepting area of the whole plant projected on a horizontal plane when retrieved from remote or proximal sensing. In the same way, when considering nitrogen fertilization applications, the link between the plant nitrogen content and chlorophyll has not been yet intensively investigated, except through simple statistical relationships limited by a reduced calibration dataset. An important limitation remains also in the parametrization of crop models, especially at global and regional scales that encompass large heterogeneities in soil and climate conditions, as well as management practices.

One important challenges is to exploit all the available information by synergistically fusing remote sensing observations of different nature in terms of spatial and spectral capabilities, as well as ancillary data coming from other sources (e.g. ground measurements networks, national statistics, historical time series …) so that crops can be better monitored and characterized. Such approaches are very promising as they are increasingly easy to implement thanks to the promotion of open source data and codes, as well as the development of ground measurement networks and stable observatory infrastructures that provide long-term records (Fegraus et al., 2012; Delgado et al., 2018; Molénat et al., 2018).

Regardless of the method used to characterize agricultural systems, continuous validation remains crucial and much more effort should be put on evaluating the performances of remote sensing products, both in qualitative and quantitative ways. This helps identifying the limitations of the products to ameliorate both the data acquisition (e.g. sensor

characteristics, conditions of acquisitions) and the algorithms by improving models or consolidating training databases for machine learning methods. Moreover defining standard validation protocols such as provided by the CEOS-LPV (Committee on Earth Observation Systems-Land Product validation) for global satellite products becomes mandatory for all remote sensing variables, regardless the sensor and the platform. Indeed, the use of remote sensing data is now democratized and bypasses the scientific community to reach the wider society (e.g. policy makers, farmers, breeders). Therefore, one of the current challenges consists of finding solutions to qualify the data so that users are able to understand which product they are using and how trustful they can be in the context of their application. New validation techniques are also being explored to make the society participating to scientific results through crowd sourcing experiments (See et al., 2016), with for instance crop maps validation through farmer surveys or mobile apps (Fritz et al., 2019) or disaster mapping. Other studies have also investigated the possibility of harvesting the information on social networks (van der Velde et al., 2012) or retrieving information from crowdsourced ground imagery (d'Andrimont et al., 2018). Some authors even claim that global land cover maps generated only from crowdsourcing are more accurate than remote sensing products (Estes et al., 2016). Indeed, the citizen contribution could be better exploited by providing more information such as for example, phenology, climate, soil condition, or presence of disease. This raises the question of the data reliability and validity when acquired via crowdsourcing. Therefore, the mutual contribution between remote sensing (as a provider of products for users) and society (as a provider of geo-located ground validation data) is only possible with a substantial effort: the remote sensing community must provide easy access, qualified and traceable products designed to given applications while the users must learn how to use them and their limitations.

Many remote sensing algorithms are well adapted to large, homogeneous areas. This can be attributed both to the past technical constraints of sensors and to the homogeneity assumption that simplifies the relationships between input and output variables. This also explains the relatively low number of studies focusing on agricultural systems composed of fragmented landscapes and smallholder farms. Investigating these agricultural systems should now become a priority, especially in developing countries where they support the food system while being highly exposed to climate change and disasters (Morton, 2007). Remote sensing algorithms must now be adapted to such type of systems characterized by large horizontal heterogeneities. Furthermore, new agricultural systems such as agroforestry are now emerging to better face both the climatic and the sustainable development constraints by mixing species together within the same field, leading remote sensing algorithms to consider both horizontal and vertical heterogeneities.

4. Conclusions and recommendations

This review presents an overview of how remote sensing can be used for agriculture. Although we did not intend to be exhaustive in terms of agricultural applications, we showed that both remote and proximal sensing are currently used at various scales and for a large range of stakeholders. While some global applications (e.g. crop mapping, yield forecasting) might be more advanced due to the historical availability of coarse spatial resolution of satellite EO data, recent years were marked by significant technological advancements which rendered the use of remote sensing data at finer spatial resolutions feasible, affordable, and profitable. However, in the last decade, studies mainly focused on showing the feasibility and the operationality of techniques and methods that had been previously developed. A large part of the effort was dedicated to machine and deep learning that answer near-real time and operational needs, taking advantage of the unique amount of data available, while fundamental research on remote sensing progressed much more slowly.

Remote sensing data are now available at multiple scales over a sufficiently large geographic extent to permit the deepening of our fundamental knowledge on the processes involved in both radiative transfer and crop functioning. However, algorithms are still dedicated to a single given scale, which generates large discrepancies between data sources and models used accross different scales. The transferability of methods across scales is still an on-going research objective (Wu and Li, 2009). Indeed, fine and local scales should help deeply refining the algorithms based on radiative transfer model inversion and improve the coupling with crop functioning model for data assimilation. The accessibility to the huge amount of data both at global (e.g. coarse resolution sensor), regional (e.g. Sentinel-2) and canopy-leaf scale (e.g. phenotyping) will also help developing machine and deep learning approaches to answer near-real time and operational needs. Mechanistic models and machine learning techniques should both be developed in parallel and in synergy to take advantage of the opportunities offered by the big data and cloud computing as well as to improve our understanding of the processes involved in crop growth.

The timeliness of the data availability and processing is crucial, both at global (e.g. food security) and field scale (e.g. management practices in agreement with the environmental context including weather events). It is thus necessary to develop real-time diagnostic and prognostic covering the period between a week after the acquisition date to the end of the crop cycle. However, the value of long-term data archive from EO coarse spatial resolution sensors should not be over-looked. These time series still have a large role, and could highly benefit from new developments for current sensors to better characterize the past agricultural systems.

Finally, remote sensing can also be seen as a tool to answer questions related to change in our society. For example, global initiatives now offer a way to provide the information everywhere at any time and accessible to everybody. It can thus be regarded as an efficient tool to empower agricultural actors to hold their engagements regarding concerted actions on global issues such a biodiversity loss, land degradation and climate change. This can help giving greater responsibility to the different stakeholders while keeping their autonomy.

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