Chapter 29

Soil health assessment and spatial characterization using remote sensing

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Abbreviations

C	carbon
RS	remote sensing
SOC	soil organic carbon
SOM	soil organic matter

29.1 Introduction

Coordinated efforts toward defining and quantifying soil health and ecosystem services have recently increased due to the potential benefit of soil health in agriculture, environmental quality, and economics. Soil health is broadly defined as the continued capacity of the soil to function as a vital ecosystem to support and sustain crop productivity, maintain environmental quality, support ecosystem services, and promote human and plant health. Soil is a complex system at the intersection of the atmosphere, lithosphere, hydrosphere, and biosphere and is critical for developing a sustainable agricultural production system. The concept of soil health emerged in the early 2000s. Now, it has been linked to the "One Health" concept, which connects the health of humans, animals, and the environment (Lehmann et al., 2020). The multidimensionality of the soil health concept allows for soil management to be aligned with sustainability and climate mitigation goals. Soil health provides a foundation for evaluating the ecosystem functions both at spatial and temporal scales. A most important achievement of the soil health framework is the addition of the most needed biological perspective to soil management and processes to address the long-term sustainability of crop production (Lehmann et al., 2020).

Soil provides goods and services (ecosystem services), including food production by controlling nutrient cycling, water flow, water quality by buffering contamination, air quality by regulating greenhouse gas emissions, and climate change mitigation by sequestering carbon (C). Soil ecosystem services are a functional response to the complex interaction of bio-physicochemical properties, land use, and agronomic management. It is important to manage soil health status for improved ecosystem services, including crop production, C sequestration (Das et al., 2022; Lal, 2016), soil organic matter (SOM), water and nutrient availability (Ankenbauer and Loheide II, 2017; Hudson, 1994), soil resilience to climate change (drought and heat waves) (Ankenbauer and Loheide II, 2017; Lal, 2016), disease suppression (Janvier et al., 2007; Raaijmakers and Mazzola, 2016), and soil erosion reduction (Das et al., 2022).

Quantifying soil health status is important for proper management and determining functional correlations with ecosystem services. Soil health is measured using multiple indicators representing nutrient cycling, biogeochemistry of carbon and nitrogen, microbial diversity, water and air quality, and soil structure, which can be grouped as physical, chemical, and biological indicators. The interrelationship of inherent bio-physicochemical soil health properties with land-use change, agronomic management, and interannual climatic variations makes it challenging at spatial and temporal measurement scales. Studies have shown that soil management practices like tillage, cover crops, and residue

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management can significantly affect soil health. Hence, a large continuum scale of measurement is needed in predicting soil health status and goods and services.

There is a collective effort toward developing indices to assess soil health holistically (Andrews et al., 2004; Bünemann et al., 2018; de Paul Obade and Lal, 2016). Developing a universal index will require an accounting of soil heterogeneity, land-use change, and climatic variation in space and time. Current in-situ measurement approaches are resource-intensive and do not provide a global understanding of soil health status. Restoration of the current cropland with an aim toward sustainable global food production and climate mitigation will require an evaluation of the success or failure of management practices. A universal index for measuring soil health status will be required to meet the global challenges. Thus, a soil health assessment must bridge the variability among soil types, land use, and climatic variability (Rinot et al., 2019). High-resolution digital soil maps based on in situ and remotely sensed data will be critical in measuring/predicting soil health status and developing global indices. The current chapter will summarize recent developments in remote sensing (RS) approaches for measuring soil health and ecosystem services, their principles, and their future perspectives. The chapter will also highlight the emerging concept of ecosystem services as commodities for future markets and discuss the possible application of RS techniques in developing markets.

29.2 Current approaches and development in soil health assessment

Soil health is a functional response to multidimensional interactions between the environment, plants, soil, and agronomic management. The changes in management practices reflect changes in the measured soil health parameters and the related ecosystem services. Soil health status is assessed by measuring different bio-physiochemical indicators, which (1) represent physical, chemical, and biological properties and processes of the soil system; (2) are sensitive to changes in soil function caused by management, land-use change, and climate change; (3) are manageable, effective, and cost-effective measurements that can be conducted at relevant space and timescale for decision-making; (4) represent the environmental vulnerability of the soil such as soil erosion risk and water and air contamination risk; and (5) represent ecosystem services such as productivity, air and water quality, soil nutrient availability, and biodiversity (Rinot et al., 2019). Some of the most used indicators in soil health assessments are SOM, soil organic carbon (SOC), aggregate stability, bulk density, soil texture, soil respiration, autoclaved citrate extractable protein, permanganate oxidizable carbon or active carbon, water extractable organic carbon and -nitrogen, water infiltration, water holding capacity, and different soil enzyme related to carbon, nitrogen, phosphorus, and sulfur nutrient cycle. However, the availability of multiple indicators also makes soil health assessment a complicated process and hard to track over extended scales of spatial and temporal variation and is also a limiting factor in the wide adoption of soil health management. Many studies are putting efforts into identifying a few critical indicators that can be used to define the soil health status in space and time (Bagnall et al., 2023; Soil Health Institute, 2022a; Soil Health Institute, 2022b)

A robust soil health assessment will depend on (1) the selection and measurement of critical indicators relevant to soil attributes of interest, which can either reflect or forecast alterations in soil due to management changes; (2) direct and indirect quantification of these indicators should able to provide a comprehensive status of the soil health and the management impact on soil ecosystem services; and (3) taking a weighted average of these scores either regionally or globally, should able to determine the soil health status on a large spatial scale and should help in designing informed management practices.

29.3 Remote sensing for soil health assessment and ecosystem services

Measuring the changes in the soil environment with respect to agronomic management can help determine and predict soil health status. In the classical approach, soil samples are collected from the site of interest under different treatments or natural conditions using a grid or zone sampling method to measure the bio-physicochemical parameters and determine the potential soil health status. However, such measurement is tedious and resource-intensive and often requires a large number of samples to capture the soil's heterogeneity; and this is where the different spectrophotometric methods are critical. Visible near-infrared reflectance spectroscopy has been successfully used to determine several soil properties (Ben-Dor et al., 2002; Gomez et al., 2008; Viscarra Rossel et al., 2009). Unique spectral signatures of the soil components and plants can be leveraged in remote sensing methods to create spatiotemporally extended digital soil maps related to land use change and specific soil properties like SOM (Ertlen et al., 2015; Heller Pearlshtien and Ben-Dor, 2020; Wang et al., 2010), SOC (Angelopoulou et al., 2019; Ladoni et al., 2010), and moisture (Mohanty et al., 2017; Wang and Qu, 2009).

Remote sensing plays an important role in studying complex environmental interactions and has been widely used in quantifying and mapping the soil's inherent properties and ecosystem services. A major benefit of the remote sensing method is the ability to capture a large continuum dataset with varying spatial and temporal resolution through frequent observation. Advancements in sensor technology and earth observation will continue to contribute extensively to research on the modeling, mapping, and valuation of ecosystem goods and services using remote sensing. Integrating remote sensing with in situ measurement has enabled measuring how different agronomic management and land use changes affect soil health properties over time. Hereafter, the chapter will discuss the measurement of a few selected soil health indicators using remote sensing.

29.4 Soil health indicators

29.4.1 Soil organic matter and carbon

SOM is a central and critical indicator in soil health measurement. SOM defines several ecosystem services, including crop production, water retention and availability (Lal, 2020), higher cation exchange capacity (Parfitt et al., 1995), high nutrient retention in the root zone, greater soil buffering capacity, improved structure and stable aggregates, and sustaining biological activity and diversity. SOM can influence environmental processes on a global scale. Soil is the largest reservoir of the C, which modifies carbon dioxide concentration in the atmosphere and can influence global warming. SOM may be lost under an intensive cropping system because of the increased C mineralization rate, especially following intensive tillage, excessive crop removal, and erosion (Ding et al., 2002; McLauchlan, 2006). Estimating SOM in chronological order with broad spatial coverage is important to define and develop a sustainable agroecosystem and carbon offset. RS, especially using spectrophotometric data, is becoming one of the most sought-after methods for monitoring and measuring SOM change on a regional and global scale. The principle behind the use of RS for SOM measurement is the distinct reflectance characteristics of soil with varying organic matter content. Studies have shown a negative correlation for SOM with soil reflectances, and have illustrated SOM is sensitive to the visible near-infrared (VNIR) (400 ∼ 1100 nm) and shortwave infrared (SWIR) (1100 - 2500 nm) spectral regions (Zhang et al., 2021). Satellites equipped with multispectral sensors such as Landsat, Sentinel-2, and MODIS can be used for SOM estimation. Several studies have used the RS data to estimate and model the SOM change (Mirzaee et al., 2016; Wang et al., 2018; Yuzugullu et al., 2020; Zhang et al., 2021). However, the prediction of SOM is challenging and susceptible to being influenced by environmental covariates including soil types (texture), seasonal conditions (soil moisture), and remotely sensed image features (pixel data) (Zhang et al., 2021). A concurrent SOM measurement from the field samples and correlating them with spectral data can be useful in training the model for better accuracy. Advanced machine-learning methods such as random forests, support vector machines, and neural networks can handle complex interaction spectral bands and soil properties and thus can be used to improve estimation accuracy (Zhang et al., 2021). Mirzaee et al. (2016) found that using Landsat 7 ETM + spectral images with an artificial neural network (ANN) for ordinary kriging can significantly improve the model's prediction. Mapping high-precision SOM maps is challenging due to the difficulty of selecting appropriate satellite data sources and prediction algorithms. Combining data from multiple sensors can provide a more comprehensive spectral range and better differentiation between SOM and other soil properties. Zhang et al. (2021) compared complete- and standard-band datasets from Sentinel-2 A and MODIS images using Google Earth Engine and created a predictive model with random forest, an artificial neural network, and support vector regression for SOM mapping. The results showed that the model based on the full-band Sentinel-2A data was best performing in SOM mapping, and the random forest was the best predictive model with the lowest root-mean-squared error (RMSE). Further, time series analysis of satellite images can help in predicting periods with minimum soil moisture, which can reduce its confounding effects on SOM prediction. Microwave sensors in SMOS and SMAP satellites can provide data on soil moisture, which can be used in correcting SOM predictions (Entekhabi, 2010). The incorporation of data on soil types, geology, and topography can further improve the model's accuracy. Geospatial databases such as SoilGrids and national soil databases can be helpful in improving the prediction (Hengl et al., 2017). The establishment of libraries that catalog spectral signatures for various soil textures can help in distinguishing between the effects of textures and organic matter on reflectance and can help in further improving the accuracy of the models (Brown et al., 2006). In the future, advances in sensor technology and data processing algorithms, coupled with ground-truthing, will enhance the precision of remote sensing-based SOM assessment.

Soil organic carbon serves as a cornerstone in the global carbon cycle and provides an index of soil health and broader ecosystem functionality. Its role underscores the significance of accurate and expansive monitoring, particularly in addressing overarching challenges tied to climate change and agricultural dynamics. The remote sensing method and

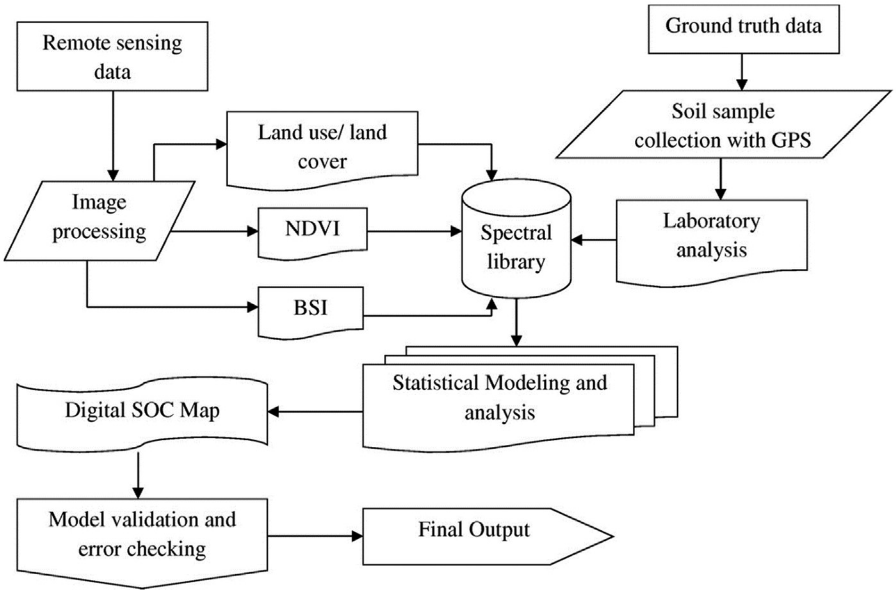

FIGURE 29.1 SOC mapping using remote sensing techniques and a multivariate regression model. *From Bhunia, G.S., Kumar Shit, P., Pourghasemi, H.R., 2019. Soil organic carbon mapping using remote sensing techniques and multivariate regression model. Geocarto Int. 34, 215–226. https://doi.org/10.1080/10106049.2017.1381179.*

in situ measurement have become integrated tools for SOC prediction and quantification (Fig. 29.1). Satellites like Landsat, Sentinel-2, and WorldView have multispectral sensors that capture data useful for SOC estimation. Several studies have used multispectral and hyperspectral remotely sensed images in SOC quantification and prediction (Angelopoulou et al., 2019; Bhunia et al., 2019; Chen et al., 2005). Development in machine learning and different geostatistical models has further improved the application of RS in developing more accurate algorithms for SOC predictions (Angelopoulou et al., 2019; Mondal et al., 2017; Odebiri et al., 2021). One such advancement is Digital Soil Mapping (DSM), which makes use of data sources, including remote sensing, terrain attributes, land use data, and other environmental covariates to derive spatial and temporal prediction of SOC.

29.4.2 Carbon flux and C sequestration

Carbon sequestration and storage efficiency can be estimated through the quantification of net ecosystem exchange (NEE) of CO_2 flux and can be used to determine the amount of atmospheric C stored in an ecosystem. Calculation of vegetative indices such as normalized difference vegetation index (NDVI), emissivity difference vegetation index (EDVI), water band index (WBI), and leaf area index (LAI) from the remotely sensed images can help in predicting the net CO_2 flux of the ecosystem (Dagg and Lafleur, 2010; Hao et al., 2012; Kross et al., 2013). Carbon sequestration provides an indirect measurement of emission reduction. Key carbon flux parameters include gross primary productivity (GPP), net primary productivity (NPP), and net ecosystem productivity (NEP). In definition, GPP refers to the total amount of C fixed by plants through photosynthesis per unit time and per unit area, and NPP is the difference between the GPP and the loss of C through plant respiration (GPP - plant respiration). Net ecosystem production is the NPP minus the respiration of the soil heterotrophic organisms, which is an indicator of the rate of net carbon flux and carbon storage (Zhao et al., 2022).

Landowners are increasingly asked about the impact of their management practices with respect to C sequestration to protect areas with high carbon densities and increase stewardship to improve soil C sequestration and storage. Measuring carbon fluxes from the agricultural field and estimating the seasonal carbon budget is critical in evaluating the sustainability of management practices with respect to crop production, carbon uptake, and greenhouse gas emissions. However, C fluxes and ecosystem services are complex, and are an integrated system of multiple variables. Process-based ecosystem models can be useful in calculating mechanistic processes and tradeoffs. However, vegetation dynamics and environmental changes are highly variable and determining factors in C fluxes. Remote sensing provides a unique opportunity to monitor changes in vegetation, soil moisture, soil temperature, and agronomic management and integrate these variables in a process-based model to improve prediction accuracy. MODIS and Landsat data can be used to estimate photosynthetic activity by calculating NDVI and Enhanced Vegetation Index (EVI), which directly relates to carbon uptake by terrestrial ecosystems (Huete et al., 2002). Soil Moisture Active Passive (SMAP) satellite can detect the changes in soil moisture, which impacts soil respiration - a key component of terrestrial carbon flux. LIDAR instruments in ICESat-2 and GEDI can be used to determine vertical forest structure information, which can be used to estimate above-ground biomass and carbon storage (Dubayah et al., 2020). In addition, the networks of flux towers, like FLUXNET, can be used to measure CO_2 exchange and to validate satellite-based estimation (Baldocchi et al., 2001). For instance, Turner et al. (2005) combined MODIS-derived vegetation indices with in situ flux tower measurements to enhance the estimation of Gross Primary Production (GPP) and Net Primary Production (NPP) across diverse sites (Turner et al., 2005). This synergy between satellite and ground data has proven invaluable in addressing the intricacies of carbon dynamics. In a comprehensive review, Schimel et al. (2015) underscored the potential of amalgamating data from optical, radar, and lidar remote sensing modalities to provide a nuanced understanding of the terrestrial carbon cycle (Schimel et al., 2015). Such a multisensor perspective compensates for the limitations inherent to individual data sources. This sentiment is echoed by Jung et al. (2011), who harmonized eddy covariance measurements from the FLUXNET network with satellite insights, painting a detailed spatial-temporal canvas of global carbon dioxide fluxes (Jung et al., 2011). Similarly, Xiao et al. (2004) adeptly harnessed both optical (MODIS) and microwave (SRTM) satellite data, and supplemented with ground observations, to model GPP in tropical forests (Xiao et al., 2005). In the challenging terrains of the Alaskan Arctic, Fisher et al. (2014) demonstrated the merits of fusing datasets from diverse remote sensing platforms, including optical, radar, and lidar, with on-ground metrics to delineate carbon flux dynamics (Fisher et al., 2014). Collectively, these studies affirm the indispensability of a comprehensive, multipronged approach, interweaving various remote sensing datasets with in situ measurements, in the quest for accurate carbon flux predictions. Niu et al. (2021) developed a "carbon and exchange between vegetation, soil, and atmosphere—ecosystem service (CEVSA—ES)" model integrating the remotely sensed leaf area index (LAI) with estimated productivity provision (primary productivity), carbon sequestration, water retention, and soil erosion. The simulated results from this study showed 95%, 92%, 76%, and 65% goodness of fit, explaining the variabilities of GPP, ecosystem respiration, net ecosystem productivity, and evapotranspiration. The CEVSA-ES model could explain 96% and 81% of the spatiotemporal variation of the observed annual productivity provision and carbon sequestration (Fig. 29.2). Several studies integrated the remotely sensed data with the process-based model to improve accuracy in predicting C flux and C sequestration (Su et al., 2022; Turner et al., 2004). Some studies have also used remotely sensed data in calculating the vegetation index and used the same in the estimation of GPP and C fluxes (Rahman et al., 2005; Xiao and Moody, 2004).

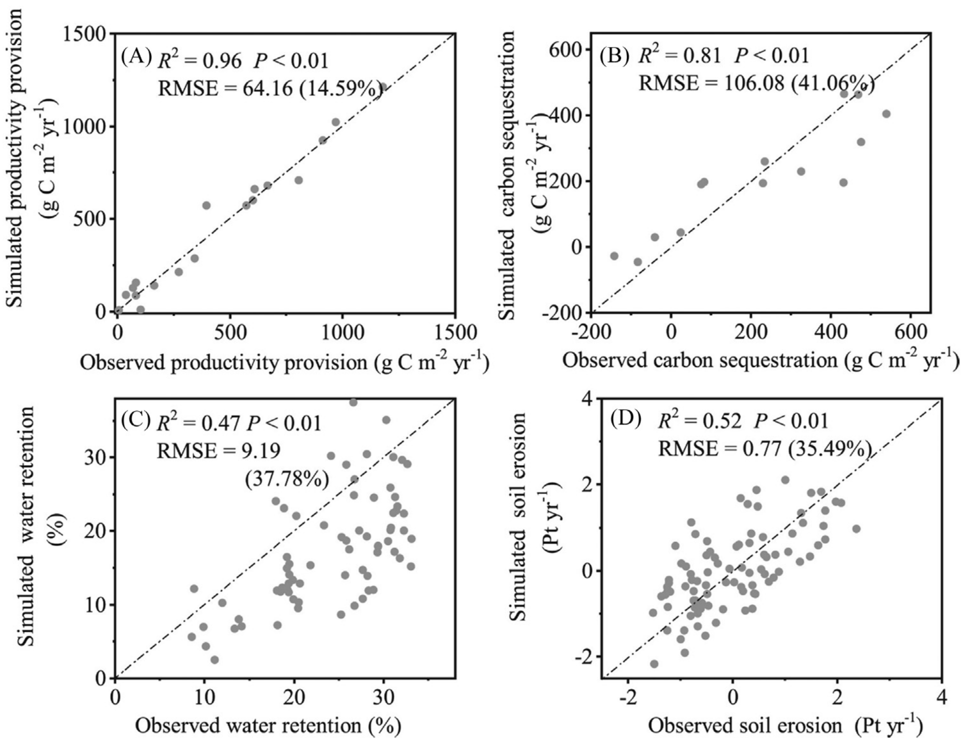

FIGURE 29.2 Performance of the CEVSA-ES model in estimating (A) productivity provision (g C m^{-2} year^{-1}), (B) carbon sequestration (g C m^{-2} year^{-1}), (C) water retention (%), and (D) soil erosion (Pt year^{-1}). CEVSA-ES, carbon and exchange between vegetation-, soil-, and atmosphere-ecosystem service. *From Niu, Z., He, H., Peng, S., Ren, X., Zhang, L., Gu, F., et al., 2021. A process-based model integrating remote sensing data for evaluating ecosystem services. J. Adv. Model. Earth Syst. 13, e2020MS002451. https://doi.org/10.1029/2020MS002451.*

29.4.3 Soil nutrient availability

Measuring soil nutrient availability and fertility is pivotal in establishing a sustainable agricultural production system and environmental quality. The success of precision agriculture depends on an efficient and accurate in-field determination of soil nutrients. The traditional grid soil sampling method for determining in-field nutrient variability is time consuming and resource expensive. A soil map at a scale of 1:31680 (a map unit size of 4.0 ha or 10 ac) has an average cost of 4.2 USD ha^{-1} or 1.7 USD/ac, and a map at a scale of 1:3000 could be 47 USD ha^{-1} (19 USD/ac) (Ge et al., 2011). Measurement of non-photosynthetic vegetation, green vegetation, NDVI, and soil spectral mixture analysis using remotely sensed data can help predict decline and improvement in soil nutrient availability (Numata et al., 2003). Remote sensing data, especially hyperspectral and multispectral images, can be used as auxiliary variables in predicting spatial variability in soil nutrients. Different narrowband and broadband vegetation indices such as NDVI, EVI, fPAR, and LAI can be used as indicators of productivity in a crop's growing season, as these can be used to determine the variation in phenology and photosynthetic potential of a crop. These variables can also indicate in-season nutrient deficiency in crops. The NDVI has been used in several studies to predict nutrient deficiency and subsequent management (Burns et al., 2022; Crain et al., 2012; Edalat et al., 2019). Remote sensing data can also provide information on soil nutrient availability. Song et al. (2018) used hyperspectral images (115 bands) from the Chinese environmental 1 A satellite as auxiliary variables in predicting the total soil nitrogen, available phosphorus, and soil-available potassium. The study used different machine learning models with the auxiliary variables for better prediction and found that the back-propagation neural network, combined with ordinary kriging, demonstrated the best predictive accuracy in mapping the spatial variation in soil nutrients. Zhang et al. (2010) used relative elevation, surface gradient, surface roughness, river dynamic index, and NDVI in describing soil total nitrogen. The study showed that soil nutrient distribution was affected by terrain and vegetation. The use of regression kriging improves the accuracy of mapping the spatial distribution. Li et al. (2021) used Gaofen-1 satellite 8m resolution multispectral images with four bands, blue, green, red, and near-infrared, to calculate the variables like NDVI, difference vegetation index, ratio vegetation index (RVI), and renormalized difference vegetation index to determine the vegetation growth, cover, yield, and crop health status, and used the variables in predicting the forest soil nutrient status (Fig. 29.3). Li et al. (2021) used the RS data as auxiliary variables with the artificial neural network model and found remote sensing variables performed better in predicting the available soil nitrogen, phosphorus, and organic matter in the upper soil layers (0−20 cm). The predictive efficiency decreases with an increase in depth, but the study found it could be improved using the terrain hydrology variables.

29.4.4 Soil moisture

Soil moisture is the most critical parameter in land-surface hydrology, which determines agricultural productivity and the well-being of animal, plant, and human health. Microwave remote sensing has been widely used in soil moisture measurement. The large difference between the dielectric constant of water and dry soil is a major advantage of using the passive microwave technique for soil moisture estimation. Low-frequency bands like X (frequency range: 8.0 to 12.0 GHz), C (frequency range: 4.0 to 8.0 GHz), and L (frequency range: 1.0 to 2.0 GHz) are widely used to detect soil surface moisture and vegetative water content. Low-frequency L bands (SMAP satellite) are mainly sensitive to surface soil moisture (Calvet et al., 2011). Several satellite-based L-band radiometers and radars, including SMOS (launched by the European Space Agency in 2009, 1.4 GHz), AQUARIUS Ocean Salinity (launched by NASA in 2011, 1.413 GHz [passive], 1.26 GHz [active]), and SMAP (launched by NASA in 2015, 1.41 GHz [passive] and 1.26 GHz [active]), were used for global monitoring of near-surface (0−5 cm) soil moisture content. The SMOS and SMAP passive radiometers currently provide 35- to 60-km-resolution soil moisture data globally at 2- to 3-day intervals (Mohanty et al., 2017). Several studies effectively used the L-band in soil moisture estimation (Escorihuela et al., 2010; Saleh et al., 2007; Schwank et al., 2010). However, there are several challenges also, including, dense vegetation can obscure soil, making it difficult for microwave signals to penetrate and reach the soil surface; roughness of the soil surface can affect the backscatter in active microwave remote sensing leading to inaccurate estimation; soil texture can also affect the dielectric properties and soil moisture affecting remote sensing, and the remote sensing are primarily captured soil moisture in the top few centimeters of the soil (Naeimi et al., 2009).

29.4.5 Soil salinity

Soil salinity is a sign of soil degradation and overall health. It can significantly reduce crop yield and negatively affect human nutrition, livelihoods, and ecosystem health. Soil salinity can destroy the soil structure, reduce water infiltration

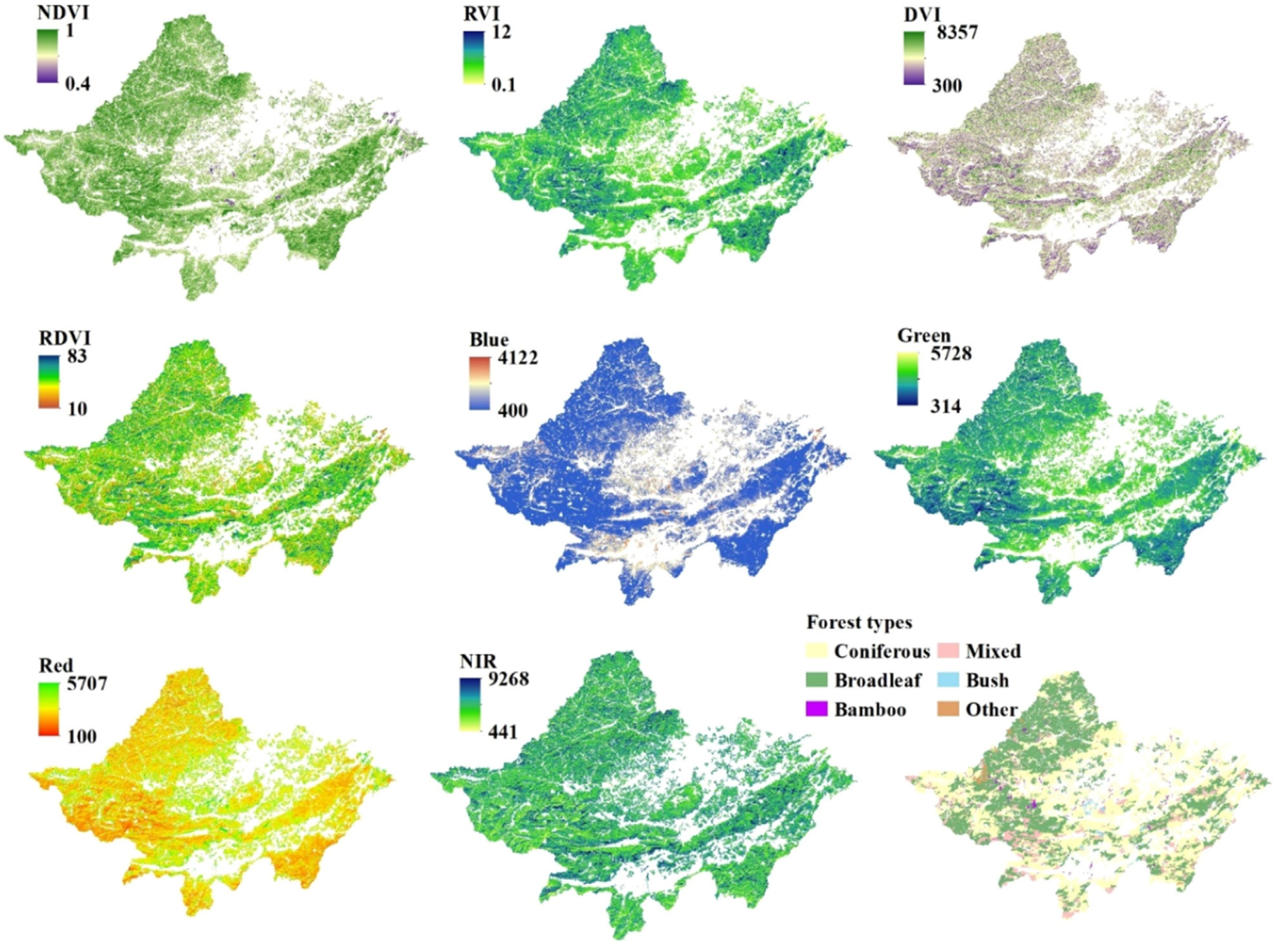

FIGURE 29.3 Remote sensing variables derived from GF- 1. *From Li, Y., Zhao, Z., Wei, S., Sun, D., Yang, Q., Ding, X., 2021. Prediction of regional forest soil nutrients based on gaofen-1 remote sensing data. Forests 12, 1430.* https://doi.org/10.3390/f12111430.

and conductance, increase erosion potential, influence soil pH and nutrient availability, and contaminate the potable water source (Sahab et al., 2021). Soil salinity is a major problem in semiarid and arid areas with low precipitation, high evapotranspiration, a high water table, and a high water-soluble salt content (Avdan et al., 2022; Wang et al., 2019). Approximately 950 million ha of land on a global scale are affected by soil salinity (Avdan et al., 2022). As an economic loss, it is estimated that secondary salinization costs $750 million per year for the Colorado River Basin in the USA, $300 million per year for the Punjab and Northwest Frontier Provinces in Pakistan, and $208 million per year for the Murray−Darling Basin in Australia for management (Metternicht and Zinck, 2003). Measuring, monitoring, and managing soil salinity for land restoration, reclamation, and sustainable agroecosystems is important.

In general, soil salinity is measured as electrical conductivity (EC), a laboratory-based method. However, collecting soil samples and performing laboratory analysis is time-consuming, not cost-effective, and cannot capture large-scale spatial variability. Remote sensing provides cost-effective, dynamic monitoring and modeling of soil salinity at a spatiotemporal scale, which can predict regions highly susceptible to soil salinity and develop subsequent management. Remote sensing also allows correlating anthropogenic covariates, such as land-use change, to better predict future scenarios. The Landsat-8 satellite (spatial resolution of 30 m) (Avdan et al., 2022) and Sentinel-2 MSI (spatial resolution of 10 m) (Farahmand and Sadeghi, 2020; Taghadosi and Hasanlou, 2021) have been effectively used in salinity studies.

A study by Avdan et al. (2022) used data from two middle (Landsat-8 OLI and Sentinel- 2 MSI) and one high spatial resolution (PlanetScope) sensors to calculate salinity indices and develop a salinity prediction model (Fig. 29.4). The study showed that the higher spatial resolution of PlanetScape showed the highest model correlation with observed and predicted values. A study by Gorji et al. (2017) used Landsat-8 TM/ETM + images to calculate the salinity index (SI), which was correlated with the EC values using regression analysis to create the soil salinity maps. The study found

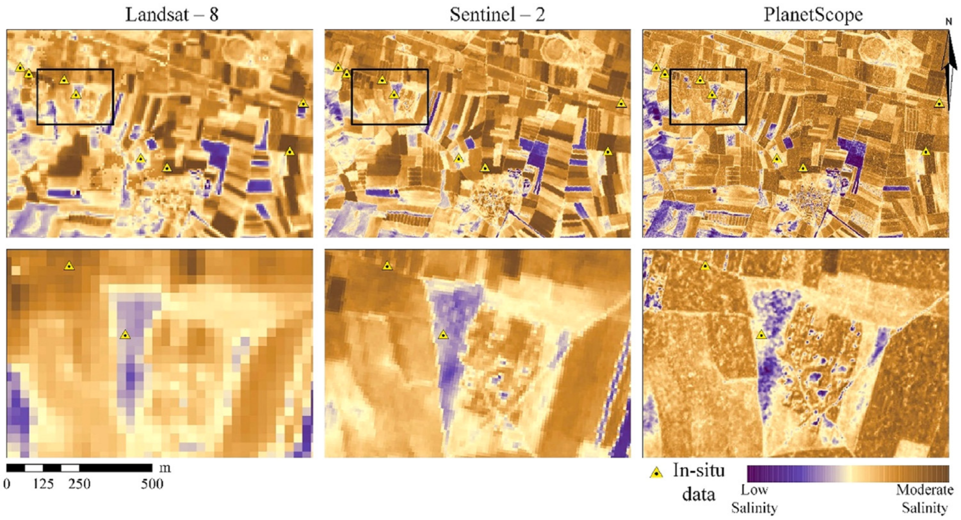

FIGURE 29.4 Predicted soil salinity map, developed with the data obtained from Landsat-8, Sentinel-2, and PlanetScoep (left to right). *From Avdan, U., Kaplan, G., Küçük Matcı, D., Yiğit Avdan, Z., Erdem, F., Tuğba Mızık, E., et al., 2022. Soil salinity prediction models constructed by different remote sensors. Phys. Chem. Earth, Parts A/B/C 128, 103230.* *https://doi.org/10.1016/j.pce.2022.103230.*

that the SI, calculated as $\sqrt{\text{Band 1} \times \text{Band 3}}$ showed the best correlation with the observed data. The study found most of the soil salinity is caused by nature when correlated with CORINE land cover data.

29.5 Soil health management

29.5.1 No-till and crop residue management

Reduced tillage and no-till (NT) are two of the most tested methods for soil erosion control and fall under the major principle of soil health, "reduce the soil disturbances." Continuous intensive tillage can significantly disrupt soil aggregate stability, increase topsoil erosion by wind and water, and reduce soil fertility. Conventional tillage can also increase SOM mineralization and reduce soil C storage (Six et al., 2000). Several studies have found that NT can improve water infiltration, and soil water content improves soil macroaggregate structure and reduces soil erosion (Blanco-Canqui et al., 2009; Sainju, 2021; Stone and Schlegel, 2010). It is important to continuously monitor changes in agronomic management to determine the success of such practices. Hyperspectral images with reflectance from visible and near-infrared regions of the electromagnetic spectrum can provide cost-effective measurement and monitoring for field operations such as fertilization, pesticide spraying, tillage, and residue management. A study by Yang et al. (2003) used hyperspectral images with 71 wave bands in the spectral range 400−950 nm and used classification and regression trees to determine conventional tillage, reduced tillage, and NT. The study used 18 replicated tillage treatment plots. They found that classification and regression trees can be used with the hyperspectral image to distinguish the tillage practices with an accuracy of 0.89 (or 89%).

Crop residue on the soil surface plays a significant role in surface energy balance, NPP, nutrient cycling, and C sequestration (Blanco-Canqui and Lal, 2009; Turmel et al., 2015). Tillage accelerates soil erosion by increasing soil exposure to wind and rain and increasing C oxidation by soil aeration and temperature. Thus, most agricultural land has less soil C than native land. Crop residue management is an integral part of soil health management, which is used along with conservation tillage or NT to improve soil health. Long-term use of NT and proper crop residue management can increase soil organic C and improve soil structure and aggregation compared to conventional tillage. The standard method of measuring the crop residue cover in a particular field is visual estimation along the transect line (Laflen et al., 1981). This technique is laborious and prone to operator bias. The current method also fails to capture the spatial variability of residue over a large farm or region. A reliable, rapid, and accurate quantification method is needed for precision farming systems and management decisions. Remote sensing can be critical in estimating/quantifying crop residue, as it can leverage the spectral signature of the crop, soil, and different plant litter components with the indices developed using visible, near-infrared, and shortwave infrared bands, like the NDVI, NDRE, normalized difference tillage index (NDTI), normalized difference index (NDI), and normalized differential senescent vegetation index (NDSVI). These indices are based on the relative difference in broadband reflectance for soil and crop residues. Few RS methods use the specific spectral signature of chemical compounds like nitrogen, cellulose, and lignin, which are highly associated with plant litter (at 1730, 2100, and 2300 nm) (Daughtry et al., 2005). The typical reflectance pattern

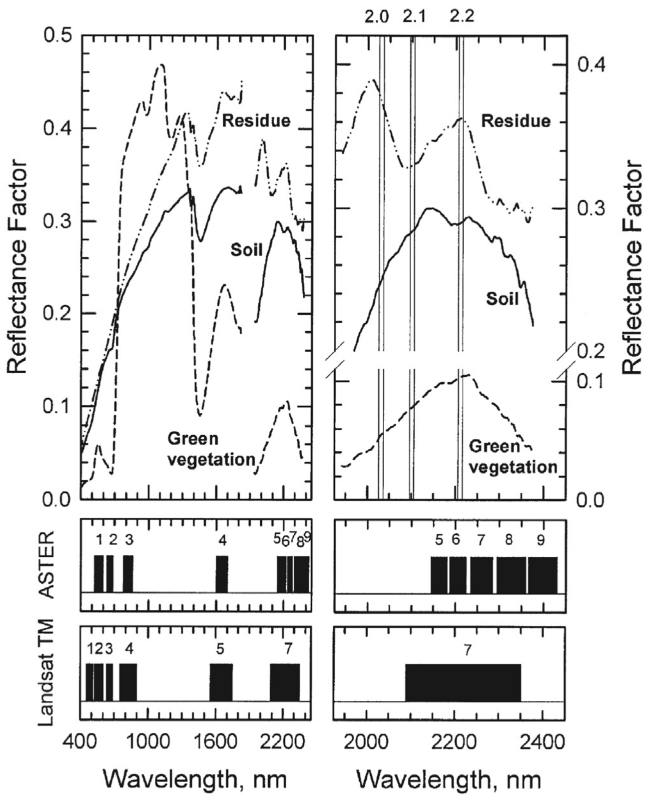

FIGURE 29.5 Typical reflectance pattern for green vegetation, soil, and corn residue. Landsat 7-Tm, ASTER, and CAI bands. *From Daughtry, C.S.T., Hunt Jr. E.R., Doraiswamy III P.C., McMurtrey, J.E., 2005. Remote sensing the spatial distribution of crop residues. Agron. J. 97, 864–871. https://doi.org/10.2134/agronj2003.0291.*

of the soil, green vegetation, and crop residue is shown in Fig. 29.5. A study by Daughtry et al. (2005) leveraged the greenness index like NDVI (related to green vegetation) and lignin and cellulose absorption indices like the cellulose absorption index (CAI) and lignin cellulose absorption index (LCAI) to distinguish between the green cover and crop residue in the agricultural field. The study found that CAI and LCAI are linearly related to crop residue. The study also showed that the spectra of tilled soil could be separated from NT soil based on the residue cover percentage. Serbin et al. (2009) developed a shortwave infrared normalized difference residue index (SINDRI), using Advanced Spaceborne Thermal Emission and Reflectance (ASTER) bands 6 and 7 for the detection of crop residue. The study found that SINDRI can be used as an alternative to CAI and LCAI in measuring crop residue cover, but the accuracy is lower compared to CAI.

29.5.2 Cover crops

Cover crops are considered one of the potential strategies to improve soil health and soil carbon. Studies have shown that cover can improve soil biological community, soil aggregate stability, SOC, increase water infiltration rate, and reduce soil erosion (Blanco-Canqui et al., 2015; Stewart et al., 2018). Soil health improvement policy, climate mitigation goals, and C sequestration demand have incentivized cover crop adoption. It is important to monitor the adoption of cover crops and estimate biomass for their potential benefits. Remote sensing can be used to identify cover crop adoption and estimate biomass (Hively et al., 2015; Hunt et al., 2011; Prabhakara et al., 2015). A study by Prabhakara et al. (2015) used ten different indices, including NDVI, green normalized difference vegetation index (GNDVI), triangular vegetation index (TVI), and visible atmospherically resistant index (VARI), calculated from a 16-band CROPSCAN sensor, to determine the cover crop growth on six fields that were planted to barley, rye, ryegrass, and triticale. The study found NDVI has a strong relationship with ground cover, and TVI was most accurate in estimating the cover crop biomass. Several studies used RS data to determine the spatiotemporal distribution and adoption of cover crops (Kc et al., 2021), the identification of cover crop species (Cruz-Ramírez et al., 2012), and termination dates (Gao et al., 2020)

29.6 Future perspective and Ecosystem Service Monetization

Conservation of the soil system and improving ecosystem services are priorities for the 21st century. The provision of ecosystem services as a commodity to economically reward resource managers is one of the most acclaimed policies to improve awareness and adoption of soil conservation practices and adoption. Awareness of climate conservation is gradually improving and subsequently expanding ecosystem markets. The last decade has seen the rapid development of research on the topic of ecosystem services and the economic value of ecosystem goods and services among decision-makers and the public (Bagstad et al., 2013; Holzman, 2012). Following the Millennium Ecosystem Assessment release in 2005, a significant increase in the number of scientific publications on the subject has been observed (Costanza, 2020; Mooney et al., 2004; Wang et al., 2021). However, ecosystem services are a complex interactive output of land use, climate, soil management, vegetation, and topo-geography along with socioecological aspects of human dimensions, which makes them hard to estimate and predict. Over the years, many scientific efforts have been made to measure soil heterogeneity and ecosystem services in situ. However, the variability in soil and the scale sought to determine the potential capacity of agroecology are very hard to accomplish using resource-intensive conventional sampling and analysis methods. Remote sensing is a potential alternative with wide applicability for assessing complex soil−plant−atmospheric interactions. The spectral signature of different chemical compounds and minerals in nature can be successfully used in estimating and predicting ecosystem services. The RS data can be used as auxiliary variables in developing comprehensive process-based ecosystem models. However, the field is still developing and needs the integration of in-situ measurement, modeling efforts, and statistical and machine learning approaches to improve ecosystem prediction and estimation implementation.

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