



Review

The Role of Earth Observation in Achieving Sustainable Agricultural Production in Arid and Semi-Arid Regions of the World

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Citation: Qader, S.H.; Dash, J.; Alegana, V.A.; Khwarahm, N.R.; Tatem, A.J.; Atkinson, P.M. The Role of Earth Observation in Achieving Sustainable Agricultural Production in Arid and Semi-Arid Regions of the World. *Remote Sens.* **2021**, *13*, 3382. <https://doi.org/10.3390/rs13173382>

Academic Editor: Karel Charvat

Received: 29 July 2021

Accepted: 17 August 2021

Published: 26 August 2021

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Abstract: Crop production is a major source of food and livelihood for many people in arid and semi-arid (ASA) regions across the world. However, due to irregular climatic events, ASA regions are affected commonly by frequent droughts that can impact food production. In addition, ASA regions in the Middle East and Africa are often characterised by political instability, which can increase population vulnerability to hunger and ill health. Remote sensing (RS) provides a platform to improve the spatial prediction of crop production and food availability, with the potential to positively impact populations. This paper, firstly, describes some of the important characteristics of agriculture in ASA regions that require monitoring to improve their management. Secondly, it demonstrates how freely available RS data can support decision-making through a cost-effective monitoring system that complements traditional approaches for collecting agricultural data. Thirdly, it illustrates the challenges of employing freely available RS data for mapping and monitoring crop area, crop status and forecasting crop yield in these regions. Finally, existing approaches used in these applications are evaluated, and the challenges associated with their use and possible future improvements are discussed. We demonstrate that agricultural activities can be monitored effectively and both crop area and crop yield can be predicted in advance using RS data. We also discuss the future challenges associated with maintaining food security in ASA regions and explore some recent advances in RS that can be used to monitor cropland and forecast crop production and yield.

Keywords: agriculture; arid and semi-arid regions; crop monitoring; remote sensing; crop yield

1. Introduction

Arid and semi-arid (ASA) regions (Figure 1) are home to approximately 2.5 billion people and occupy 41% of the Earth's land surface [1]. Arid regions occur within zones with rainfall of 0–300 mm and an inter-annual variability of 50–100%, whereas semi-arid regions occur within zones with rainfall of 300–600 mm and an inter-annual variability of 25–50% [2,3]. According to the latest report on the state of food security and nutrition in the world, one in 10 people now face hunger or food shortages [4]. To mitigate this risk,

there exist efforts to increase agricultural production, but this is not happening at the same rate as population growth [5–8].

The majority of poor people live in ASA regions of the world where primary productivity is achieved through agriculture and farming at small or large scales [9]. Although the contribution of agriculture to the economy may vary among the ASA regions across the world, it is generally crucial to economic growth. For example, agriculture contributes a substantial share of Africa's economy (15% of total GDP) [10]. The agricultural sector in Africa provides employment to half of the total labour force [11] and provides livelihoods for the majority of small-scale farmers within rural areas [10]. In Sub-Saharan Africa, 80% of agricultural land is smallholder-based and employs more than 175 million people [12]. Similarly, in the Middle East and North Africa (MENA) regions, agriculture contributes only 13% to GDP, but is of strategic importance to the economy [13]. Therefore, any disruptions in the agriculture sector will have far reaching impacts on food security in these regions.

In addition to the above, most undernourished people in Africa are based in Sub-Saharan countries where there was an increase of about 32 million undernourished people since 2014 [4]. Moreover, in 2019, Asia was home to more than half of the total number of undernourished people in the world (381 million) [4]. This is mainly because ASA regions face several natural and human challenges including, but not limited to, irregularities in climatic conditions and the impacts of conflict or political instability [14–17]. A combination of these factors contributes to an increase in resource or food security vulnerabilities that are poorly understood at varying geographic scales [18–20]. To monitor, understand and mitigate the impact of these factors on regional and global food security, reliable and timely information is needed by countries and decision-makers [21].

At the national scale, greater information is needed by agricultural decision-makers to support investment and policy decisions that could have potential implications for their country's food security. For example, several studies have assessed agricultural vulnerabilities, but most of these analyses were performed at the country level [22–24]. This is because crop databases are usually available at the country level, and information on finer spatial coverage cannot be obtained [25]. In addition, regional crop data are collected sparsely and available for only a limited period [26]. At sub-national (local) scales such information can include primary information on crop health status, spatial extent, crop type suitability and expected crop yield [27,28]. Having such information in advance of harvest and at finer spatial resolution is essential to make decisions about how much food is to be stored, imported and exported and to make a general assessment of food losses in times of natural and anthropogenic crises [29].

Increasing local agricultural production is key to providing long-term food security for communities [30]. Maintaining food security requires frequent data for monitoring and assessment [31]. Generally, ground surveys are the most common approach for assessing food insecurity in rapid emergencies such as floods, droughts and conflict situations [32]. However, when access is restricted, or on-the-ground assessment is not possible due to insecurity issues, the World Food Programme (WFP) often uses mobile technology to reach vulnerable populations [33]. Ground surveys (or the use of mobile technologies) have several limitations: (i) it is expensive and time-consuming to collect ground data [34], (ii) surveys provide only a snapshot or cross-sectional assessment, (iii) the spatial extent of data collection is limited [34]. In addition, it can be challenging to forecast food security based on ground survey data accurately and efficiently at national or global scales due to then often vast spatial coverages and heterogeneity involved [34]. Providing inaccurate food security information could bias decision-making and result in severe food shortages and price fluctuations. For example, Jayne and Rashid [35] showed that overestimating production by 13% and underestimating consumption by 8% can result in a 21% food shortage, which additionally could lead to steady rises in food prices if food aid or trade is absent.

RS has great potential to overcome some of the above limitations as it can provide data at various temporal and spatial scales. RS is highly suitable for monitoring agricultural activities, predicting yield [36] and predicting seasonal production, and these are driven by climatic variables, the physical landscape and agricultural management [37]. This paper firstly describes several important characteristics of agriculture in ASA regions that require monitoring to improve agricultural management. Secondly, it demonstrates how freely available RS data can improve agricultural efficiency through a cost-effective monitoring system that can complement traditional approaches for collecting agricultural data. Thirdly, it illustrates the challenges of employing freely available RS data for mapping and monitoring crop area, crop status and forecasting crop production and yield in these regions. Lastly, the common approaches used in these applications are evaluated, and the challenges associated with their application and possible future improvements for these regions are discussed. Further, this study explores the agricultural challenges of smallholder farming in the Middle East and Africa and provides potential RS-based solutions and suggested improvements. These ASA regions are targeted since data coverage is scarce, incomplete and the datasets are low quality generally [26]. Moreover, their food security is often under constant threat due to their fragile climatic conditions and political environments [4].

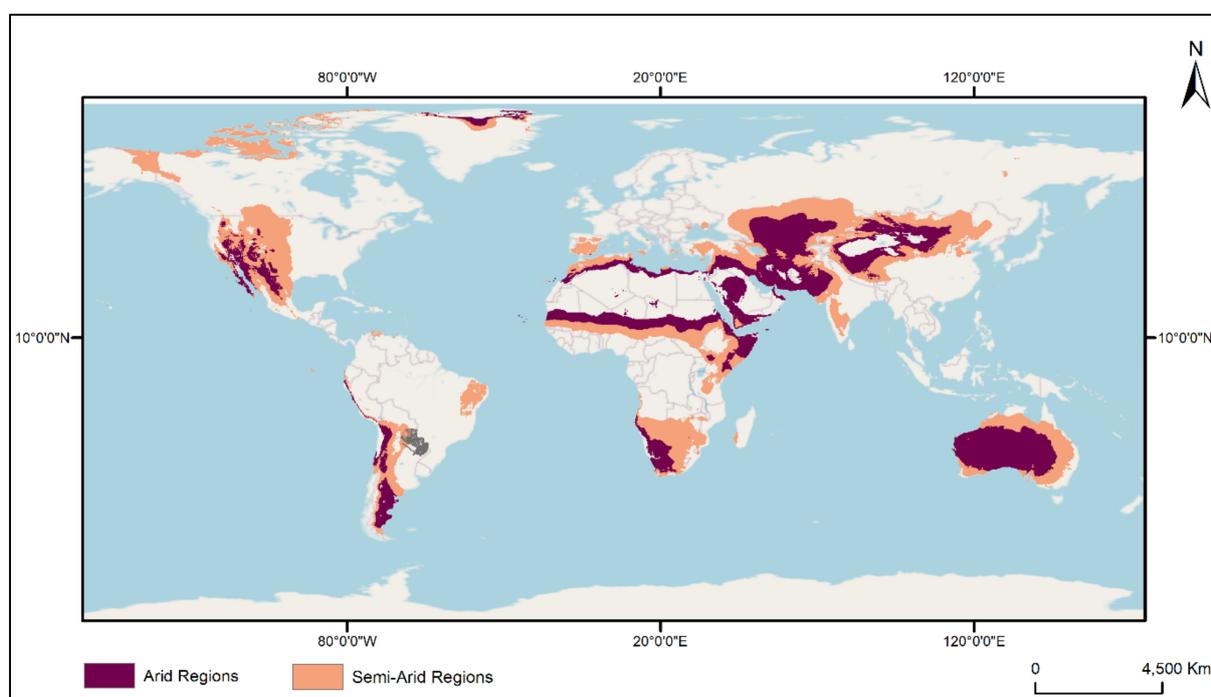


Figure 1. Global distribution of arid and semi-arid (ASA) regions [38]. It is estimated that arid regions cover around 28 million km² while semi-arid regions cover around 46 million km².

2. Enhancing Food Production through RS Applications in Agriculture

Monitoring agricultural activities through traditional approaches can be challenging because of the following. Firstly, usually agricultural regions are large, and their effective monitoring requires repeated coverage [31]. Secondly, yield prediction is based commonly on monitoring the growth phases of crops and information obtained via traditional approaches is often limited [36]. In addition, challenges with geographic access to many areas in ASA regions due to political instabilities mean that RS data can be used as a potential source to complement traditional approaches for collecting agricultural data. There are many RS applications in agriculture. We selected and explored a few key applications to keep the paper concise. In particular, this paper focuses on the three main RS applications in Middle Eastern and African ASA countries including identifying and estimating crop area, monitoring agricultural status, and modelling and forecasting future crop yield. These

RS applications are critical in these regions since the smallholder farming system is complex and agricultural management is heterogeneous [39]. In addition, due to their fragile climatic conditions and often political instabilities, these areas are prone to many crises which can induce regional food insecurity [29]. Despite these challenges, several regional characteristics can influence the RS proxies that are used as a base for these applications which will be discussed in the following sections. In such conditions, and due to lack of data and resources, RS can provide remote and cost-effective solutions and improve regional food security [40]. Table 1 provides a summary of the role of remote sensing applications for increasing agricultural productivity and food security.

Table 1. The role of remote sensing for monitoring agricultural productivity and increasing food security.

RS Applications	Activities
Identifying and estimating crop area	<ul style="list-style-type: none"> • Cropland mapping and crop type classification [41–43]. • Estimate and forecast crop area before harvest time [39,44]. • Obtain sufficient data in insecure regions [45,46].
Monitoring agriculture crop status	<ul style="list-style-type: none"> • Differentiate among diseases and pests, infectious severities and map their spatial distribution [47–50]. • Assess before and after intervention crop condition, water and nutrient requirement [51–53].
Modelling and forecasting future crop yield	<ul style="list-style-type: none"> • Fine resolution local and regional yield map and advance yield prediction [29,36,54]. • Generate yield gap map and underperforming croplands [55,56]. • Obtain sufficient crop production data in insecure regions [57,58].

2.1. Identifying and Estimating Crop Area

Information on crop area and crop type are vital for land management and trading. Even in well-developed and well-organised countries, ground-based crop area estimates are often not available until a few months after harvest [39]. Obtaining a reliable figure before harvest is a major challenge and, at the same time, vital for the formulation of policymaking and decision-making [39,59]. Figure 2 shows the processing steps typically applied to remote sensing data to predict crop type.

Compared to a humid environment, ASA regions typically have specific climatic and regional characteristics which pose many challenges to accurately identifying and estimating crop area [39,59]. Due to considerable changes in the spatial and temporal distribution of rainfall, and the fact that the majority of smallholder farms in ASA regions rely on rainfall to start planting, identifying and estimating crop area can be difficult [39]. Spatial and temporal variation in rainfall could result in variation in agricultural management, crop choice, heterogeneity in the cropping system, crop phenology and productivity [60,61]. Often phenological variables are used as a critical base to identify and estimate crop area. However, in ASA regions, these variables could vary substantially among the countries and inter-annually [39,61,62]. Therefore, attempting a single classification approach at a regional or global scale could result in inaccurate outputs. For example, Qader et al. [39] developed a phenological approach in Iraq which produced a coefficient of determination with the official statistical crop data at the governorate level twice that of the global MODIS land cover classification. At the global scale [63] and in particular for Africa, large discrepancies were observed between current continental and global landcover maps in terms of the overall and spatial distribution of croplands. Thus, current global crop maps might not perform well in these regions and a customised approach should be considered to derive a sufficiently accurate crop map.

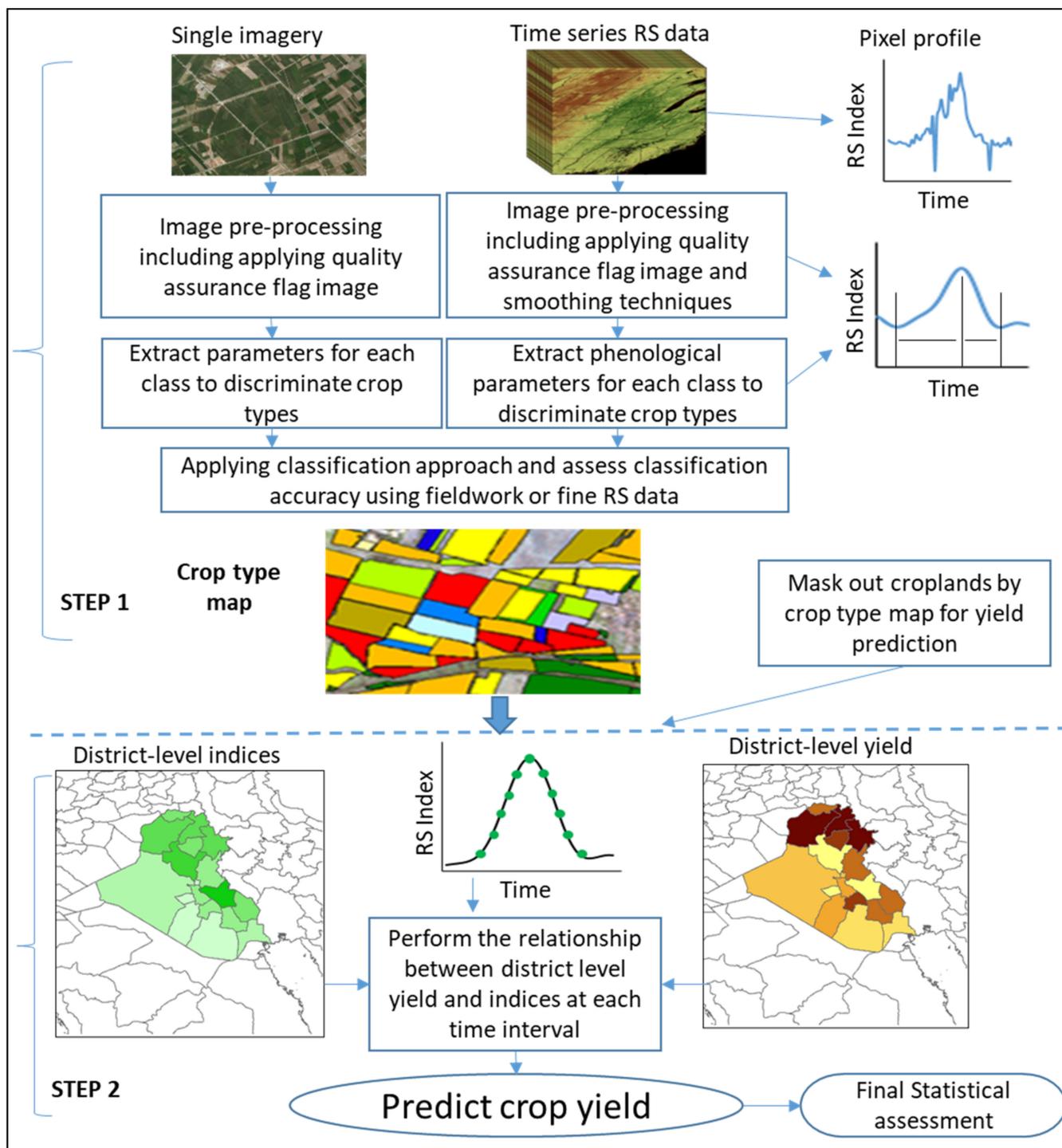


Figure 2. Schematic diagram illustrating the general methodology for using RS data to forecast crop yield. Step 1: processing steps typically applied to remote sensing data to predict crop type and Step 2: processing steps typically applied to forecast crop yield.

Another challenge for accurate identification and estimation of crop area in ASA regions is the common practice of the agriculture fallow system [39,44]. Depleted soil, lack of adequate water distribution and the existence of pests and diseases have led smallholder farmers in ASA regions to practice a biennial fallow system from which many fields remain uncultivated annually. For example, the extent of fallow fields in the cropland class was estimated to be 63% (403,617 km²) for the Sahel region in 2017 [44]. The spatial heterogeneity and spectral mixture of these fields with croplands could result in the inaccurate classification of croplands from the analysis of RS data in these regions. In addition, there may be a scarcity of field samples to train the classifier in the large and heterogeneous landscapes of ASA regions, particularly in insecure and fragile regions. For example, in the spatial distribution of the training data used in the global MODIS land cover classification, Iraq and Syria were excluded [64].

For crop classification, single date and multi-temporal (time-series) imagery can be used to estimate and classify crop area. Due to inter-annual spatio-temporal variation in cropping area in ASA regions due to significant climatic variability and crop rotation practices, time-series RS data can be used with several benefits. At different phenological stages, time-series data can be analysed selectively to provide more useful vegetation spectral information relative to single date imagery [65,66]. In addition, temporal analysis aids in the discrimination of various crop classes based on differences in their growth patterns. Furthermore, multi-temporal data increase the information of the imagery as the sun angle changes with the season, which affects vegetation surface reflectance [67]. Lastly, time-series data provide a larger number of predictor variables applicable to machine learning classification approaches, thus, potentially increasing classification accuracy [68,69].

Several studies have demonstrated that RS approaches can be used to produce reliable crop area estimates and crop type classification [39,70–72]. In the ASA region of Arizona, nine major crop types were able to be classified using a RS approach with an overall accuracy of >85% [41]. In Turkey, overall accuracies above 90% were achieved between cropland area estimates using RS data and official statistics [73]. In addition, RS can provide a powerful solution in some ASA regions where access is restricted due to security issues and remoteness. In Northern Bosnia, Witmer [45] managed to identify abundant agricultural land before, during and after the 1992–1995 war using Landsat imagery with an overall accuracy of 82.5%. Similarly, due to the 1991–1994 Nagorno Karabakh conflict between Armenia and Azerbaijan high farmland abandonment rates of more than 60% were found in the conflict zone using multi-temporal Landsat imagery [46]. Therefore, RS can provide timely information on crop area and crop types in various circumstances where traditional approaches are not feasible, and such information can help reshape policy decisions and enhance food security [39,46].

2.2. Monitoring Agricultural Crop Status

Crop status encompasses growth, health and seasonal progress. Abiotic factors (e.g., nutrients, irradiation, temperature and water) and biotic factors (e.g., diseases, pests and weeds) can have a significant impact on crop status [74]. Information on crop growth conditions has been identified as an essential indicator for yield forecasting and food security assessment [75]. A wide range of commercial crops might be affected by plant diseases and pests, which can pose major risks to final crop yields. Based on recent estimates, annually around 20–40% of global crop production is lost to pests, and plant diseases and invasive insects are responsible for global economic losses of around USD 220 billion and USD 70 billion, respectively [76]. In their technical report, del Rio and Simpson [77] indicated that as a result of climate change, around 16 of the most important crops grown in the Sahel are affected by 100 diseases. Among the 34 phytoplasmas (microorganisms) ribosomal groups reported globally, 14 were reported in Middle Eastern countries [78]. In addition, aggressive strains of fungal disease such as wheat rusts have been detected in East Africa and the Middle East, and they can cause devastating losses to wheat crops [79]. According to the USDA report, in 2010–2011, yellow rust outbreaks reduced wheat production to

35% below record levels in Syria and 5% in Turkey compared to the previous year [80]. In Africa, maize yield was reported to have decreased by between 30% and 60% due to grey leaf spot (GLS) [81]. Furthermore, poor crop protection practices in these regions might have contributed to the impact of pests and diseases on crop yield. For example, due to pest attack, losses in rice of up to 51% were recorded in West Africa, and of 22% in Oceania [82]. Lastly, due to its rapid spread and significant impact on crop yield loss, there exists global concern about fall armyworm. Hruska [83] indicated that fall armyworm is spreading rapidly in Africa, the Near East and Asia. It has been predicted that in the major maize-producing countries in SSA, annual yield losses attributable to FAW are between USD 2.5 and 6.2 billion [84]. Despite these losses, insufficient knowledge regarding the probability of occurrence, direction and distribution of pests and diseases, as well as the severity of their impact on crops, has posed further challenges to control such issues. Therefore, an efficient monitoring system is needed to provide cost-effective solutions in these poor regions.

In terms of weather-related disasters, drought is one of the key risks to global crop yield. Globally, it is estimated that droughts have caused a 5.1% cereal yield loss during the past four decades [85]. ASA regions are more exposed to the risk of drought and its consequences because they are the most vulnerable regions to climate variability and climate change [15,86,87]. At the regional scale, agricultural drought has affected around 810 million ha (27.5% of Africa) and around 452 million ha (33.8% of the total Arab Region) [88]. In addition, the frequency and intensity of extreme weather events such as droughts and floods are projected to increase in the Middle East and North Africa regions due to climate change [89,90]. The increasing frequency and intensity of extreme weather events have caused extreme declines in crop yields in ASA regions. For example, in Iraq, the drought in 2008–2009 caused a loss of crop production of 51% compared to the previous year. In Turkey, total crop yields declined substantially, costing USD 1–2 billion and with 435,000 farmers affected [91]. Sultan et al. [92] found that the average annual production losses across West Africa in 2000–2009 associated with historical climate change, accounted for USD 2.33–4.02 billion for millet and USD 0.73–2.17 billion for sorghum. To mitigate such events, cost-effective real-time monitoring systems should be put in place to warn local authorities. Meng and Wu [93] stated that crop biomass condition information at the pre-harvest stage can be used to indicate potential food shortages and surpluses and support related policy-making decisions. A recent systematic review of extreme weather events (EWE) in agriculture found that monitoring and detecting the impacts of EWE using RS techniques is still underdeveloped [94]. It was also highlighted that gaps still exist concerning the impacts of EWE on major cash crops and the agronomic dynamic of EWE in developing countries [94]. In addition, other researchers found that RS data can be used to monitor and assess the impact of EWE on crop yield [95,96]. Therefore, accurate and timely detection, monitoring and mapping of crop health, growth and seasonal progress due to crop diseases and pests and extreme weather events is critical for forecasting and assuring food security.

The occurrence of diseases and pests on crops and the canopy surface can cause changes in chemical concentration, pigments, nutrients, gas exchanges and water uptake [97,98]. In response, the colour and temperature of the canopy may change and result in variation in canopy reflectance characteristics, which can be measured by RS [98,99]. Existing RS approaches can discriminate various diseases and pests, evaluate their infection severities and map their spatial distribution at various scales [47–50]. For example, using Landsat images, it was possible to map the severe infestation of the take-all disease in wheat [100]. Ma et al. [50] developed a multi-temporal satellite data-based early detection method for regional mapping of powdery mildew disease. In addition, remote sensing estimation of soil moisture was used to plan desert locust surveys for preventive management [101]. Furthermore, it was demonstrated that fine spatial and temporal resolution remotely sensed data can be used to monitor crop condition, assess crop damage in flood areas [52], assess crop condition in relation to soil moisture [51], and monitor crop condition

in extreme events such as droughts [102]. Furthermore, RS can be integrated into early warning systems to alert local and international authorities about any negative events that could impact overall production. For example, Anomaly hot Spots of Agricultural Production (ASAP) is an early warning system focused on anomalies in agricultural production that aims to prevent food security crises and anticipate resource needs [103].

2.3. Modelling and Forecasting Future Crop Yields

The need to model and forecast crop yields in ASA regions is increasing in parallel with recent and projected changes in land use and climate and with recent crises in food security (Cole et al., 2018). Forecasting crop yield is essential for the agricultural and economic stability of regions and is vital to sustaining global food security [29]. Farmers, policymakers, investors and hedgers need accurate and timely information on crop quality and supply. This information can help governments and local agencies to ensure strategic contingency plans to redistribute food during times of crisis [29,104].

Different seasonal yield forecast methods have been highlighted in the literature. Traditionally, crop yield forecasts are conducted by farmers through the within-season assessment of crop growth. However, this approach is uncertain and inconsistent due to subjective expectations of crop yield [105]. For decades, statistical modelling to forecast crop yield has been used globally. Statistical regression-type models applied to agrometeorological data provide a common approach to seasonal yield forecasting [106,107]. The simplicity of the approach has resulted in wide application. However, low accuracy in other areas outside the boundaries of the observed data is a real concern [108]. Considering the climatic variabilities and frequent extreme events that occur in ASA regions, such an approach might be insufficiently robust for crop yield forecasting. Numerous seasonal yields forecasting approaches were also developed based on statistical models using RS data [29,109,110]. In addition, crop growth simulation models have been used for crop yield forecasting. Such models can incorporate soil, crop, management and weather information as inputs to simulating plant growth [111], and the models can incorporate RS derivative datasets to forecast crop yield [112]. However, the high data demands and computational costs of these models make them generally challenging to employ in some regions for which data are sparse. Therefore, in model selection, regional constraints should be considered carefully.

It is important to consider which spatial, temporal, and spectral characteristics of RS data meet ASA regional requirements for monitoring food security. For example, medium-to-coarse spatial resolution satellite sensor data (e.g., MODIS) were commonly used in crop early warning systems by many aid organisations (e.g., FAO) to mitigate food insecurity [113]. In contrast, moderate spatial resolution imagery such as Landsat and Sentinel are required if the study aims are localised at the farm level. Several researchers have evidenced the advantage of RS approaches for forecasting crop yield in these regions. For example, a simple remote sensing vegetation index approach can produce more accurate crop yield maps compared to the agro-meteorological Simple Algorithm for Yield (SAFY) model [114]. Beyond the generally utility of RS-derived *vegetation* indices to estimate and forecast crop yield, other RS indices can also be used to forecast crop yield more accurately in ASA regions. For example, MODIS-derived NDVI, the two-band enhanced vegetation index (EVI2) and the Normalised Difference Water Index (NDWI), in association with county-level data, were used to develop empirical models predicting soybean and maize yield in the central United States [36]. Although, in general, large correlations ranging from $R^2 = 0.69$ to 0.73 were found between the forecasted and ground crop yield for all indices, NDWI was more accurate in semi-arid regions due to its sensitivity to low-density agriculture, irrigation and variation in the liquid water content of vegetation canopies [36]. Therefore, prior consideration should be given to determine the best RS index to use for each specific regional climatic condition.

In some ASA regions where geographical access and availability of data are limited, RS can also provide a vital alternative source of information. In Syria, sparsely available, inaccurate or non-existent ground agriculture data, due to regional instability, has limited the capacity of the country to monitor and increase agricultural productivity. However, this information can be replaced through RS techniques. With the advantage of available RS data in the conflict zone of Syria, summer crop yield was predicted with a significant correlation ($p < 0.05$) between the predicted and ground crop data [57]. The method was also shown to be advantageous for forecasting crop yield during conflict years where reported data are questionable. Similarly, Jaafar and Ahmed [17] indicated that RS can provide a credible prediction of agricultural yield in the absence of statistics. They utilised MODIS and Landsat imagery to predict wheat and barley in ISIS-controlled areas in both Syria and Iraq for the years 2014–2015 and irrigated summer crop yield in Northeast Syria [17]. Therefore, RS-derived information can be critical to monitoring agricultural productivity and assessing food security where traditional data collection might not be viable due to natural or anthropogenic crises.

A leading and successful system which has provided crucial data on food insecurity is the Famine Early Warning System Network (FEWS NET). This system integrates remote sensing and ground observation data to undertake crop assessment in areas where crop production is a concern. It is a lead provider of early warning and analysis on food insecurity which has provided evidence-based analysis for around 34 countries. Figure 2 illustrates the general methodology for forecasting crop yield using RS data.

To understand in more depth the application of RS in yield forecasting, a search for relevant peer-reviewed research articles was conducted in Scopus. This was achieved by using several specific search terms within Scopus; for example, “crop yield prediction” or “yield estimation” or “yield prediction” and “remote sensing” or “Earth observation” and “arid and semiarid regions”. In addition, abstract revision and title screening were performed to pre-select the most relevant papers in which RS data were used for this purpose in ASA areas. In total, 50 research articles were selected as summarised in Table 2.

Table 2. Summary of relevant papers using RS data to predict yield for different crop types.

	Location and Extent	Crop Type	RS Data/Resolution	Method	Model Performance	Reference
1	Pakistan, Faisalabad district	Maize	Landsat 8/30 m	Least absolute shrinkage and selection (LASSO) regression model	$R^2 = 0.95$	[115]
2	U.S., Midwest	Maize and soybean	MODIS/250 m	Random forest and other models (e.g., LASSO, ridge regression (RIDGE))	$R^2 = 0.78$	[116]
3	Brazil, Rio Grande do Sul (RS) state	Soybean	MODIS/250 m	Multivariate OLS linear regression, random forest and LSTM neural networks	RMSE = 0.4 Mg ha ⁻¹	[117]
4	Canada, Prince Edward Island and Brunswick provinces	Potato	NDVI was measured using the FieldScout CM NDVI Meter/0.5 m	Support vector regression (SVR), linear regression (LR), elastic net (EN), k-nearest neighbour (k-NN)	RMSE = 4.62 t/ha	[118]
5	China, North China Plain	Wheat	MODIS/250 m	Support vector machine (SVM), Gaussian process regression (GPR), and random forest (RF)	$R^2 = 0.75$	[119]
6	Iran, Boshruyeh city	Barley	Sentinel-2/10 m	Gaussian process regression algorithm, decision tree, K-nearest neighbour regression	$R^2 = 0.84$	[120]
7	Middle Amur Region, Khabarovsk Municipal District	Soybean	MODIS/250 m	Linear regression model	RMSE = 0.13 t/ha	[121]
8	Senegal, parkland of Central Senegal	Millet	Sentinel-2/10 m	Linear regression model	RRMSE = 28%	[122]
9	Wisconsin, Arlington Agricultural Research Station	Alfalfa	UAV-Based Hyperspectral Imagery/few cm	Ensemble modelling	$R^2 = 0.874$	[123]
10	South-East of Queensland in Australia, Bundaberg	Sugarcane	Integrating Landsat-8 and Sentinel-2	Linear regression model	$R^2 = 0.87$ (RMSE = 11.33 t·ha ⁻¹)	[124]
11	South Wales, Moree Plains Shire	Wheat	Sentinel-2/10 m	Multivariate linear regression	$R^2 = 0.93$ (RMSE = 0.64 t/ha)	[125]
12	China, County Level (e.g., Hebei, Henan, Shandong)	Winter wheat	AVHRR/0.05 arc degrees	Long short-term memory (LSTM) neural networks	$R^2 = 0.77$ (RMSE = 721 kg/ha)	[126]
13	Uruguay, Soriano site (field scale)	Winter wheat	Landsat-7, Landsat-8/30 m	Simple regression method	RMSE = 966 kg ha ⁻¹	[127]
14	Florida, the University of Florida in Citra site	Strawberry	UAV	Region-based convolutional neural network (R-CNN)	84.10%	[128]
15	US, Midwestern	Maize	Landsat 5, 7, and 8/30 m	Simple Algorithm For Yield estimates (SAFY)	$R^2 = 0.62$	[129]
16	China, Central China Agricultural University	Oilseed rape	UAV	Partial least squares regression, support vector machine regression, artificial neural network	$R^2 = 0.7$	[130]

Table 2. Cont.

	Location and Extent	Crop Type	RS Data/Resolution	Method	Model Performance	Reference
17	Heilongjiang province in northeast China, Hongxing Farm	Corn	HJ-1 satellites/30 m	Nonlinear regression	$R^2 = 0.92$	[131]
18	Australia, districts and countries	Canola and wheat	MODIS/250 m	C-Crop model	$R^2 = 0.81$	[132]
19	The U.S., national and county levels	Maize	MODIS/250 m	Linear trend model	RMSE = 4.37 bushels per acre	[133]
20	Germany, Osnabrück University of Applied Sciences in Belm	Wheat	UAV-Based Hyperspectral Imagery	Partial least-squares regression, multiple linear regression	$R^2 = 0.79$	[134]
21	North China Plain	Wheat	MODIS/250 m	MCWLA-wheat model	$R^2 = 0.42$	[135]
22	madison county, Molly Caren Farm	Corn	Aerial imagery and LiDAR data	Random forest (RF); neural network (NN); support vector machine (SVM)	$R^2 = 0.53$	[136]
23	U.S., central Iowa	Corn	MODIS/250 m; Landsat-Sentinel2-MODIS	Linear regression approach	$R^2 = 0.62$	[137]
24	U.S., west Tennessee	Cotton lint	Landsat 8	Artificial neural network	$R^2 = 0.86$	[138]
25	China, Qutang Town, Haian city	Wheat	HJ-CCD/30 m	Wheat Grow model	RMSE = 0.92, 1.12 g m ⁻²	[139]
26	Australia, Acacia Hills, Northern Territory	Mango	World View-3/0.31 m	Artificial neural network	$R^2 = 0.60$	[140]
27	Hungary, country	Wheat, rapeseed, maize and sunflower	MODIS/500 m	Multiple linear regression models	$R^2 = 0.817, 0.827, 0.88, 0.76$	[141]
28	Brazil, Itirapina—SãoPaulo	Sugarcane	UAV	Multiple linear regression	$R^2 = 0.69$	[142]
29	Australia, northern grain-growing region	Wheat	Landsat 5 and 8/30 m	Linear mixed-effects model	RMSE = 0.79 Mg/ha	[143]
30	Laos, Rice Research Center	Rice	MS-720 spectroradiometer	partial least-squares regression	$R^2 = 0.873$	[144]
31	Bangladesh, Munshiganj District	Potato	Landsat 7 and 8/30 m	Regression analysis	$R^2 = 0.81$	[145]
32	China, Rugao city, Jiangsu province	Rice	UAVs	Multiple linear regression function	$R^2 = 0.75$	[146]
33	USA, inot Noir vineyards in California	Grape	Landsat 7 and 8/30 m	Linear function	$R^2 = 0.8$	[147]

Table 2. Cont.

	Location and Extent	Crop Type	RS Data/Resolution	Method	Model Performance	Reference
34	USA(Illinois) and China (Heilongjiang Province)	Corn	MODIS/250 m	Simple linear regression models	$R^2 = 0.87, R^2 = 0.68$	[110]
35	China, Yangling District	Wheat	(HJ-1A/B/30 m, RADARSAT-2/8 m)	Regression models	$R^2 = 0.68, RMSE = 1.77 \text{ ton/ha}$	[148]
36	Brazil, São Paulo State	Sugarcane	MODIS/250 m	Neural network wrapper	$R^2 = 0.61$	[149]
37	U.S., Missouri Mississippi	Corn	MODIS/250 m	Regression analysis	R^2 value of 0.85	[150]
38	Franc, near Toulouse, regional scale	Maize	Formosat-2, SPOT4-Take5, Landsat-8 and Deimos-1. SPOT4-Take5	Simple Algorithm For Yield estimates (SAFY)	$R^2 = 0.96; RRMSE = 4.6\%$	[109]
39	India, Arrah district	Wheat	SkySat imagery/2 m	Linear regression model	$R^2 = 0.62$	[151]
40	Spain, IRTA Research Station in Gimenezells	Maize	UAV/0.15 m	Linear-plateau models	$R^2 = 0.74$	[152]
41	Saudi Arabia, Wadi Al-Dawasir area south of Riyadh	Potato	Landsat 8/30 m, Sentinel2/10 m	Linear regression analysis	$R^2 = 0.65, R^2 = 0.65$	[153]
42	Southern Africa, Harare centre	Maize	UAV/10 cm	Multiple variances analyses	$R^2 = 0.69$	[154]
43	Turkey, Seyhan Plane	Wheat, corn, cotton	Landsat/30 m	Stepwise linear regression	$R^2 = 0.67, R^2 = 0.5, R^2 = 0.7$	[155]
44	Syrian and Lebanese territories	Crop	MODIS/500 m	Regression analysis	$R^2 = 0.85$	[57]
45	China, Northeast China Plain	Maize	MODIS/500 m	RS-P-YEC model	$R^2 = 0.827$	[156]
46	U.S.A.	Corn	MODIS/500 m	Convolutional architecture for fast feature embedding, support vector machine	$R^2 = 0.742, R^2 = 0.820$	[157]
47	Pakistan, Sindh province	Rice	Landsat ETM+	Regression models	$R^2 = 0.875$	[158]
48	China, Huaibei Plain	Winter wheat	SPOT-VEGETATION	Regression tree	$R^2 = 0.93$	[159]
49	China, Baizhuang town of Anyang county	Winter wheat	SPOT-5 image/10 m	Linear function	$R^2 = 0.64$	[75]
50	U.S.A.	Corn	MODIS/Terra (or Aqua)/250 m/500 m	The simple bias correction algorithm	$RMSE = 0.83 \text{ t ha}^{-1}$	[160]

3. Remote Sensing Challenges and Solutions to Increase Agricultural Productivity

3.1. Data Issues

Regardless of geographic area, developing high-quality RS approaches to monitor agricultural activities that can produce accurate and robust results may require standardised inputs and, thus, data pre-processing [161]. Any uncertainties within the data inputs and pre-processing steps may result in low predictive accuracy. Here, we outline briefly some of the key challenges for RS-based approaches.

3.1.1. Lack of Quality and Quantity, and Inconsistency, in Ground Data

Agricultural monitoring systems in many countries still rely on traditional approaches (i.e., ground-based) for data collection and reporting. Such data are costly, time-consuming and prone to large errors due to incomplete ground observations and subjectivity, and often do not exist or are inaccessible in many ASA regions [162–164]. In Sub-Saharan African regions, crop data are generally incomplete and of low quality [26]. In addition, the low quality of labelling in the reference dataset may also influence mapping accuracy [165–167], and low accuracy of species identification may arise due to lack of skill in the data collectors [168,169]. Nevertheless, such data are used widely to support supervised classification and yield modelling based on remote sensing data. Furthermore, errors and biases might come from the scale mismatch between the sensor spatial resolution and cropland patterns, particularly for smallholder-dominated systems [60,170]. Although there have been substantial advances in RS, collecting the ground data required to calibrate and validate RS algorithms across large spatial areas and temporal scales remains a major constraint. Low quality and unrepresentative samples in the ground data could result in substantial uncertainties in the RS-based prediction models. This is challenging when mapping continuous variables such as yield at the farm-scale level, where the calibration data often are unreliable or non-existent.

3.1.2. Atmospheric and Reflectance Biases in Earth Observation Data in ASA Ecosystems

In general, careful choice of appropriate satellite sensor data and remotely sensed techniques should be made for monitoring agricultural productivity in ASA regions. Shao and Dong [171] stated that in ASA regions, the frequent occurrence of dust storms needs to be considered and treated carefully in image pre-processing. The dust storm phenomenon can affect image quality by altering spectral reflectance posing major challenges to RS applications in agriculture. Since the information recorded by remote sensors represents both atmospheric and surface interactions, accurate translation of sensor radiance to estimates of surface radiance (and reflectance) by subtracting atmospheric noise is crucial for the effective use of remote sensing data in this context [172]. Interaction of the reflected signal with atmospheric particles such as aerosols can affect measurements. Therefore, careful parameterisation of aerosol characteristics over time and space is needed to derive surface reflectance accurately, for estimating vegetation biophysical properties [173]. Inaccurate estimation of vegetation biophysical properties could deleteriously affect RS-based prediction models [174].

For a given atmospheric condition, several atmospheric radiative transfer scripts have been developed to model gaseous absorption, and molecule and aerosol scattering [175,176]. Houborg and McCabe [172] combined satellite and Aerosol Robotic Network (AERONET) data to parameterise aerosol properties and atmospheric state parameters, and the NDVI was computed using the corrected reflectance data with the smallest errors (3–8% mean absolute deviation). The approximate aerosol retrieval algorithm errors of different sensors such as MODIS, MERIS and MISR can range between $\pm 0.05 + 0.2T550$ [177–179]. The quality of the retrieval process depends mainly on adopting suitable techniques for making use of multi-angular and multi-sensor data streams [180]. Several factors can impact retrievals such as bright desert conditions [181] and high aerosol loadings [172]. Therefore, attention needs to be paid to selecting the most appropriate aerosol model [176]: a fixed aerosol model should be avoided [182].

The above early pre-processing of satellite sensor images is particularly important in agricultural applications since several vegetation indices are applied commonly for monitoring purposes, in which multi-temporal images are used [183]. In ASA ecosystems, generally the spatial density of vegetation is low [184,185] and this presents another challenge to applying RS in these areas. The sparse coverage of vegetation can reduce the contribution of the area-averaged reflectance of a pixel [183]. In addition, due to the lack of organic matter content, particularly in desert areas, soils in these regions tend to be bright and heterogenous mineralogically [184]. All these factors can increase the possibility of excluding the spectral contribution of vegetation within individual pixels [186–188], particularly if an adequate spatial and spectral resolution was not selected. In addition, vegetation in dry environments is different to its humid counterparts, mainly due to a stronger red edge [184,189]. Moreover, rapid phenological change due to climatic conditions can have a significant impact on the overall brightness and spatial and temporal interspecies spectral variability [184,189]. Therefore, achieving accurate RS-based estimates in these regions requires a good understanding of regional constraints and the selection of appropriate satellite sensor data types and RS techniques that suit the condition.

3.1.3. Small Agriculture Field Size and Insufficient Spatial Resolution

A challenge for estimating crop area and type in some ASA regions, or parts of these regions, is the heterogeneity of the landscape and small agricultural field size [39,190]. To monitor crops efficiently, a high temporal revisit frequency over large geographic areas is required [135]. Meanwhile, this limits the spatial resolution of the data. A coarse spatial resolution (e.g., <1 km) is problematic where pixels are mixed, meaning that several signals corresponding to different land cover types occur within a single pixel, for example, due to small agricultural field sizes [39]. In small agricultural field sizes, this variability is especially problematic as the spectral reflectance in gridded moderate resolution products such as from the MODIS and Medium Resolution Imagen Spectrometer (MERIS) sensors may represent a mix of different land covers and heterogeneous cropping patterns [191,192]. In addition, due to the similar spectral signature and phenological characteristics between natural vegetation and crops, or among different crop types (particularly wheat and barley), their discrimination in these regions is often challenging. Although, hard classification (i.e., the allocation of whole pixels to single crop classes) of moderate spatial resolution (30 m) images produced accurate results for commercial farming, it could not deal with mixed pixels in Ethiopia because of the small agricultural field size [193]. For countries located in semi-arid zones such as Zambia, Niger and Cameroon in Africa, croplands were mostly confused with savannas and grasslands, followed by shrublands and woodlands [194]. This might be due to the relatively coarse spatial resolution of the data used, as such data have intrinsic limitations in highly heterogeneous and intermixed land uses [39,194]. Part of this confusion might be related to differences in crop calendars; classification accuracy can be affected where agricultural practices are advanced or delayed in some areas. In addition, the spatial and spectral resolutions of satellite sensor data also play a vital role in controlling the level of detail at which land cover can be classified. In Iraq, previous phenological classification [39,195] produced low accuracy in discriminating between wheat and barley due to the large spatial and spectral resolution of the input data. Due to the relatively small field size with respect to MODIS pixels (250 m), it was challenging to discriminate between the two crop types [39,195]. In contrast, greater accuracy was achieved in Iran with higher spatial resolution data [196].

Figure 3 depicts the differences in spatial coverage between gridded Landsat (30 m) and MODIS (250 m) data over fine spatial resolution ArcGIS basemap imagery for some agricultural lands in (a) North-East Aleppo, Syria, (b) South-East Mosul, Iraq and (c) South Sanaa, Yemen. The figure shows clearly that the individual MODIS pixels cover several agricultural fields (Figure 3a–c), which may be used to plant different crops. However, Landsat could be more representative of the small agricultural parcels. Even if the same crop is planted in several fields covered by a MODIS pixel, within-pixel variability in crop

phenology timing may exist if different agricultural management practices are applied. The mismatch in spatial resolution between remotely sensed data and the small agricultural field sizes makes it challenging to derive crop phenology, identify crop types and estimate crop yield accurately.

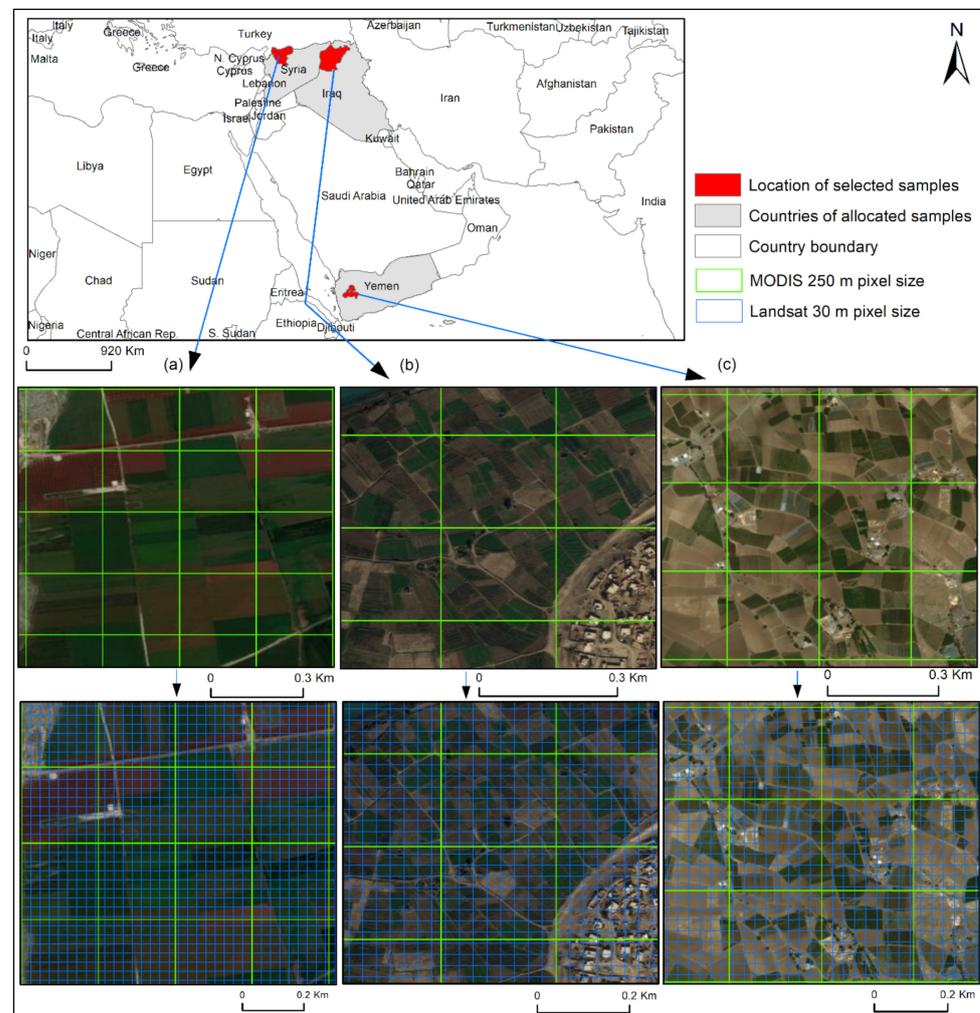


Figure 3. Three fine spatial resolution ArcGIS basemap images (<1 m) of agricultural areas selected from the Middle East to illustrate the agricultural detail that is lost within MODIS and Landsat images. Grid outlines representing 250 m pixels from MODIS and 30 m pixels from Landsat are shown overlaid on the base images. (a) North-East Aleppo, Syria, (b) South-East Mosul, Iraq and (c) South Sanaa, Yemen. (Service layer credits: Esri, DigitalGlobe, GeoEye, Earthstar, Geographics, CNES/Airbus DS, USDA, USGS, AiroGRID, IGN, and the GIS User community).

3.2. Remote Sensing Solutions and Future Applications

3.2.1. New RS Techniques and Data to Increase the Accuracy of Crop Area Estimation

To overcome the issue of low classification accuracy, previous approaches used fusion approaches to combine the fine spatial resolution of data from the Landsat series of sensors with the high temporal frequency of data from coarse resolution sensors such as MODIS (Gao et al., 2006; Lobel et al., 2013), to provide fused datasets suitable for application to ASA regions. Such products could have added value for a wide range of applications which need both fine spatial and temporal resolutions, such as land cover classification and forecasting crop yield. One approach, called the spatial and temporal adaptive reflectance fusion model (STARFM) is based on a spatial relationship between Landsat and MODIS spectral reflectance. The MODIS spectral reflectance can be downscaled to the spatial resolution of Landsat obtained at the same dates [197]. An extension of STARFM was

developed to increase the accuracy of predicting the surface reflectance of heterogeneous landscapes (ESTARFM) [198]. Linear mixture models were also used to downscale MERIS data to a Landsat-like spatial resolution and results indicated that vegetation dynamics, discrimination of crop types, phenology and rapid land cover types could be monitored effectively [199,200]. Luo et al. [201] developed a new fusion approach called STAIR and claimed that based on intensive experiments the approach not only captures useful texture patterns but also predicts reflectance accurately in the generated images, with a significant improvement over the classic STARFM algorithm. In addition, new products such as Sentinel data provided by the European Space Agency (ESA) have become accessible to the RS community, which increases the spatial and spectral resolutions available for applications such as complex land cover/land use mapping, forest monitoring and change detection. Data extracted from Sentinel imagery, such as from Sentinel-2 and 3, can be used in isolation or combined, or both can be combined with MODIS and Landsat 8 through data fusion techniques. Recently, although agricultural field sizes are generally small in Sub-Saharan Africa, with a fine spatial and temporal resolution achieved by integrating Sentinel-2 data it was possible to disentangle agricultural land into the cropped and fallowed classes [44]. Such discrimination can help capture crop fallow rotation which can provide key information on how cropland expansion and intensification affects environmental parameters such as crop yield, soil fertility and local livelihoods in low-income regions such as the Sahel [44]. Cubesat Enabled Spatio-Temporal Enhancement Method (CESTEM) was also developed recently, producing Landsat 8 consistent and atmospherically corrected surface reflectance, but at the spatial scale and temporal frequency of the CubeSat observations [202]. In their paper, application of this approach to an agricultural dryland system in Saudi Arabia was demonstrated in which CubeSat-based reproduction of Landsat 8 consistent VNIR data was achieved with an overall relative mean absolute deviation of 1.6% or better, even when the Landsat 8 and CubeSat acquisitions were temporally displaced by >32 days. Wang and Atkinson [203] also developed a new fusion method using Sentinel datasets in which more accurate results were produced compared to the existing STARFM. In their research, spatio-temporal fusion was considered to fuse S-2 and S-3 to generate nearly daily S-2 images which may be useful for monitoring highly dynamic environmental, agricultural or ecological phenomena. This approach may be suitable for forecasting crop yield in ASA regions in the future.

3.2.2. New Freely Available RS Data to Improve Monitoring Agricultural Crop Status

It has been noted that the majority of efforts to map and monitor crop diseases and pests are conducted in small plots, or at least over small areas [204–206]. This is because such monitoring often relies on commercial satellite sensor images with the necessary spectral and spatial/temporal resolution to capture the detailed variation of interest. Thus, upscaling or adopting these approaches for other areas is challenging due to the large cost constraint. In addition, in other research where freely available coarse spatial resolution images were used, low accuracies were produced. Therefore, future research must investigate the utility of freely available data, such as from Landsat 8 and Sentinel, which provide adequate spatial and temporal resolution images across the world. For example, a new spectral index for detecting wheat yellow rust using Sentinel 2 was developed by Zheng et al. [207], and the overall identification accuracy for the index was 84.1%. It is also important to stress that ecologists, botanists and remote sensing scientists should come together and agree on standardised variables that are critical for mapping and monitoring crop disease and pests using remote sensing data. Isip et al. [208] indicated that Sentinel 2-based VIs can be used for the detection of twister disease in the field since it gives greater discrimination and high accuracies.

3.2.3. Utilising the Improved RS Sensing Capabilities to Increase the Accuracy of Crop Yield Forecasting

Over the past decades, most research in RS on crop yield modelling and forecasting has emphasised the use of greenness and biomass as the basis for prediction [209,210]. Since the

environment in ASA regions is highly variable, an alternative way to increase the accuracy of yield forecasts based on RS is to use vegetation biochemical and biophysical parameters as a surrogate for crop yield. Chlorophyll is a key biochemical parameter, which has a large correlation with crop productivity [211]. Many studies revealed the close relationship between chlorophyll content and Gross Primary Yield (GPP) [211,212]. Thus, compared to leaf area index (LAI) or biomass, the chlorophyll content might be expected to be more associated with crop yield. The chlorophyll content of vegetation, which is a function of the biochemical variables of chlorophyll concentration and the biophysical variable of LAI, can be surrogated by the MERIS Terrestrial Chlorophyll Index (MTCI) [213]. Zhang and Liu [214] assessed the potential of an MTCI-based model for crop yield forecasting compared to the NDVI in Henan Province, China from 2003 to 2011. Their results revealed several advantages of the MTCI-based model compared to the NDVI-based model, such as (i) larger significant correlation coefficient and smaller error; (ii) crop yield could be forecasted 30 days earlier than using the NDVI-based model. Although the results were not compared to other VIs, a significant correlation between MTCI and crop yield was found at regional scales for the state of South Dakota, USA [213]. Thus, considering its consistently large correlation with final crop yield, satellite-derived chlorophyll content should be further adapted for crop yield forecasting in ASA regions.

Until now, we have focused on reflected light in the solar spectrum as the main source of information about vegetation conditions. However, there is an extra source of information in the spectral range of the optical and near-infrared, providing information about vegetation productivity. This source of information is associated with the emission of fluorescence from plant leaf chlorophyll; re-emitted energy because this part of the spectrum cannot be utilised in carbon fixation [215]. In addition, observational evidence in many studies revealed that chlorophyll fluorescence provides information independent of reflectance-based spectral VIs [216]. Recent advances in remotely sensed-based approaches to estimate photosynthesis relied on the flux of chlorophyll fluorescence emitted by the canopy, which has provided opportunities to develop many satellite retrieval algorithms [217–219]. Recently, Guan et al. [220] provided a framework to correlate solar-induced fluorescence (SIF) retrievals and crop yield. Crop productivity was estimated for 2007–2012 using spaceborne SIF retrieval from the Global Ozone Monitoring Experiment-2 satellite in the United States. Besides the more accurate and efficient measurement of crop productivity compared to traditional crop monitoring approaches, the SIF was able to capture information on the impact of environmental stresses on carbon use efficiency and autotrophic respiration, with considerable sensitivity of both to high temperatures. These outcomes revealed new opportunities to increase the accuracy of crop yield forecasting and increase understanding of crop yield responses to different climatic conditions in ASA regions.

4. The Role of Government, Investors, Policymakers and NGOs

In 2002, the gap between Earth observation and science policy in the UK was analysed and the conclusions are still valid globally in which the major limitation has been the lack of a mature marketplace [221]. After 20 years, Tonneau et al. [222] came to a similar conclusion in their recent policy brief: existing shared data and products are not meeting African demands due to the large gap between Earth observation capabilities and science policy in African countries and the major role of Global North institutions in shaping technology resource strategy [222,223]. In recent decades, RS technology has advanced significantly and large numbers of satellite sensor images at different spatial and temporal resolutions have been made freely available to help tackle multiple challenges in different application domains [224]. Although the current data offered by various satellite sensors have met the requirements of many agricultural decision-makers, such techniques and data have not been incorporated effectively into the agricultural monitoring systems of many ASA countries [29,223]. There are several possible explanations for this, including (i) lack of capacity to understand and analyse RS data and (ii) lack of infrastructure such as compu-

tational power and internet connectivity to process and analyse the data [223,225,226]. Full exploitation of EO data for agricultural monitoring will require sufficient networking and training, and financial support to purchase or update equipment to be able to keep up with advances in technology. Moreover, training opportunities provided by university courses in RS and geomatics, and training centres in spatial technologies, are in short supply and located in only a few countries in Africa [222]. Furthermore, often the people who have taken advanced courses and training are assigned to unrelated tasks and are not able to employ or transfer the knowledge gained [225].

It does not matter how advanced the RS technology becomes and how many free satellite sensor images will be available in the future if the capability to adapt them is insufficiently developed. Governments and their associated infrastructures in ASA regions might lack the required trained staff or general understanding to be able to take advantage of such techniques to improve agricultural management and incorporate them into their decision-making processes [223]. Thus, governments and investors should focus on strengthening the capacities in ASA countries by providing technical assistance and training. This will help these countries to provide and sustain solutions to issues that are appropriate for their socio-economic and environmental security. Governments and NGOs should rely on free, fine spatial and temporal resolution satellite sensor imagery such as from Landsat and Sentinel to make the systems sustainable and scalable and economically viable. In addition, all satellite sensor images (recent and historical) should be easily accessible. In particular, satellite sensor images and their derivative products that are financed by public funds should be publicly available. Some of these challenges and suggestions could be true in other parts of the world, but due to security issues, lack of data and data quality issues, the fragile environment and lack of resources in these regions, adopting RS approaches to monitor agriculture productivity is urgently needed.

5. Conclusions

ASA regions are defined by low water availability caused by the hydrological balance of precipitation and evapotranspiration and may also be affected by irregularities in the timing of precipitation, resulting in the frequent occurrence of droughts [1,29]. Unfortunately, many ASA regions of the world are also politically insecure particularly in the Middle East and Africa. Both factors make these regions vulnerable in terms of crop production and yield. RS could be used to provide the required comprehensive spatial coverage and timely crop monitoring data on which to base early warning systems that could significantly reduce food insecurities. Here, we demonstrated how RS can help improve the monitoring of agricultural productivity and, thereby, the assessment of food security by providing key information through the growing cycle. This information includes identifying and estimating crop area, monitoring agricultural crop status and health, and forecasting future crop yield. We demonstrated that RS data can play a vital role, especially given that the required data are freely available for these applications. Moreover, the data are available in both 'normal' situations and 'abnormal' situations where access to other data is greatly restricted due to natural and anthropogenic crises. Since data from relatively new satellite sensors such as Landsat 8 and the Sentinel series of sensors are available for free and their specification can meet the requirements of these agriculture applications, ASA countries should consider adopting these datasets into their national agricultural monitoring systems. Researchers and investigators should also explore new RS techniques in these regions such as to provide more accurate and robust results to support national policy and local decisions in support of ensuring food security. We recommend that researchers should focus on integrating already available fusion techniques into their agricultural monitoring systems such as creating fused datasets with a fine spatio-temporal resolution that can be used to classify crop type and forecast crop yield for ASA regions. Lastly, governments and funders should provide adequate resources to strengthen the capacity of countries in ASA regions. In particular, they should aim to provide the appropriate training and infrastructure that will enable them to incorporate such data and techniques into their

agricultural monitoring systems to increase the capability to forecast crop production and yield and reduce food insecurity.

Author Contributions: Conceptualization, formal analysis and visualization, S.H.Q.; reviewing papers to generate Table 2, N.R.K.; writing original draft preparation, S.H.Q. and P.M.A.; funding acquisition, S.H.Q.; writing-review and editing, J.D., N.R.K., V.A.A., A.J.T. and P.M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by UK Research and Innovation GCRF 323036/ARCP011217. V.A.A. is funded through a Wellcome Trust Training Fellowship (# 211208).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Gaur, M.K.; Squires, V.R. Geographic Extent and Characteristics of the World's Arid Zones and Their Peoples. In *Climate Variability Impacts on Land Use and Livelihoods in Drylands*; Springer: Cham, Switzerland, 2018. [CrossRef]
- Barakat, H.N. Arid lands: Challenges and hopes. In *Earth System: History and Natural Variability-Vol. III*; EOLSS publishers/UNESCO: Oxford, UK, 2009.
- International Fund for Agriculture Development (IFAD). The Rangelands of Arid and Semiarid Areas. 2000. Available online: <https://www.ifad.org/en/> (accessed on 13 March 2021).
- FAO; IFAD; UNICEF; WFP; WHO. The State of Food Security and Nutrition in the World 2020. In *Transforming Food Systems for Affordable Healthy Diets*; Food and Agriculture Organization of the United Nations (FAO): Rome, Italy, 2020.
- Wise, T.A. *Can We Feed the World in 2050? A Scoping Paper to Assess the Evidence*; GDAE Working Paper No. 13-04; Global Development and Environment Institute, Tufts University: Medford, MA, USA, 2013. Available online: https://ciaotest.columbia.edu/wps/gdae/0029266/f_0029266_23757.pdf (accessed on 16 August 2021).
- Godfray, H.C.J.; Beddington, J.R.; Crute, I.R.; Haddad, L.; Lawrence, D.; Muir, J.F.; Pretty, J.; Robinson, S.; Thomas, S.M.; Toulmin, C. Food Security: The Challenge of Feeding 9 Billion People. *Science* **2010**, *327*, 812–818. [CrossRef]
- Guillou, M.; Matheron, G. *The World Challenge to Feed 9 Billion People*; Springer: New York, NY, USA, 2014. Available online: <http://www.springer.com/us/book/9789401785686> (accessed on 16 May 2021).
- Röös, E.; Bajzelj, B.; Smith, P.; Patel, M.; Little, D.; Garnett, T. Greedy or needy? Land use and climate impacts of food in 2050 under different livestock futures. *Glob. Environ. Chang.* **2017**, *47*, 1–12. [CrossRef]
- FAO; IFAD; UNICEF; WFP; WHO. *The State of Food Security and Nutrition in the World 2019 Safeguarding against Economic Slowdowns and Downturns*; FAO: Rome, Italy, 2019.
- OECD/FAO. Agriculture in Sub-Saharan Africa: Prospects and challenges for the next decade. In *OECD-FAO Agricultural Outlook 2016–2025*; OECD Publishing: Paris, France, 2016. [CrossRef]
- International Monetary Fund (IMF). *International Jobs Report*; Economist Intelligence Unit: Washington, DC, USA, 2015.
- AGRA. *Africa Agriculture Status Report: Climate Change and Smallholder Agriculture in Sub-Saharan Africa*; Alliance for a Green Revolution in Africa (AGRA): Nairobi, Kenya, 2014. Available online: <https://hdl.handle.net/10568/42343> (accessed on 10 February 2020).
- International Food Policy Research Institute (IFPRI). Unlocking the Potential for Agricultural Development in the Middle East and North Africa. 2018. Available online: <https://www.ifpri.org/blog/unlocking-potential-agricultural-development-middle-east-and-north-africa> (accessed on 14 April 2021).
- Blench, R.M. *Aspects of Resource Conflict in Semi-Arid Africa*; Overseas Development Institute: London, UK, 1996.
- Sarr, B. Present and future climate change in the semi-arid region of West Africa: A crucial input for practical adaptation in agriculture. *Atmos. Sci. Lett.* **2012**, *13*, 108–112. [CrossRef]
- Schwabe, K.A.; Connor, J.D. Drought Issues in Semi-arid and Arid Environments. *Choices* **2012**, *27*, 1–5.
- Jaafar, H.H.; Woertz, E. Agriculture as a funding source of ISIS: A GIS and remote sensing analysis. *Food Policy* **2016**, *64*, 14–25. [CrossRef]
- Brinkman, H.J.; Hendrix, C.S. *Food Insecurity Violent Conflict: Causes, Consequences, and Addressing the Challenges (Occasional Paper n° 24)*; World Food Programme: Rome Italy, 2011. Available online: https://documents.wfp.org/stellent/groups/public/documents/newsroom/wfp238358.pdf?_ga=2.110043398.2008393740.1629366699-1914409899.1629366699 (accessed on 15 November 2020).
- Sharma, K.K.; Dumbala, S.R.; Bhatnagar-Mathur, P. Biotech Approaches for Crop Improvement in the Semi-arid Tropics. In *Plant Biotechnology*; Ricroch, A., Chopra, S., Fleischer, S., Eds.; Springer: Cham, Switzerland, 2014.

20. Falkenmark, M. Growing water scarcity in agriculture: Future challenge to global water security. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **2013**, *371*, 20120410. [[CrossRef](#)] [[PubMed](#)]
21. Beeri, O.; Peled, A. Geographical model for precise agriculture monitoring with real-time remote sensing. *ISPRS J. Photogramm. Remote Sens.* **2009**, *64*, 47–54. [[CrossRef](#)]
22. Brooks, N.; Adger, W.N.; Kelly, P.M. The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Glob. Environ. Chang.* **2005**, *15*, 151–163. [[CrossRef](#)]
23. Naumann, G.; Barbosa, P.; Garrote, L.; Iglesias, A.; Vogt, J. Exploring drought vulnerability in Africa: An indicator based analysis to be used in early warning systems. *Hydrol. Earth Syst. Sci.* **2014**, *18*, 1591–1604. [[CrossRef](#)]
24. Naumann, G.; Spinoni, J.; Vogt, J.; Barbosa, P. Assessment of drought damages and their uncertainties in Europe. *Environ. Res. Lett.* **2015**, *10*, 124013. [[CrossRef](#)]
25. Thornton, P.K.; Jones, P.G.; Alagarswamy, G.; Andresen, J. Spatial variation of crop yield response to climate change in East Africa. *Glob. Environ. Chang.* **2009**, *19*, 54–65. [[CrossRef](#)]
26. Fuglie, K.O.; Nicholas, E.R. Resources, Policies, and Agricultural Productivity in Sub-Saharan Africa. 2013. Available online: https://www.ers.usda.gov/webdocs/publications/45045/35520_err145.pdf?v=0 (accessed on 16 August 2021).
27. Shafi, U.; Mumtaz, R.; Garcia-Nieto, J.; Hassan, S.A.; Zaidi, S.A.R.; Iqbal, N. Precision Agriculture Techniques and Practices: From Considerations to Applications. *Sensors* **2019**, *19*, 3796. [[CrossRef](#)]
28. Karthikeyan, L.; Chawla, I.; Mishra, A.K. A review of remote sensing applications in agriculture for food security: Crop growth and yield, irrigation, and crop losses. *J. Hydrol.* **2020**, *586*, 124905. [[CrossRef](#)]
29. Qader, S.H.; Dash, J.; Atkinson, P.M. Forecasting wheat and barley crop production in arid and semi-arid regions using remotely sensed primary productivity and crop phenology: A case study in Iraq. *Sci. Total Environ.* **2018**, *613–614*, 250–262. [[CrossRef](#)] [[PubMed](#)]
30. Kaiser, M.L. Food Security: An Ecological-Social Analysis to Promote Social Development. *J. Community Pract.* **2011**, *19*, 62–79. [[CrossRef](#)]
31. Enenkel, M.; See, L.; Karner, M.; Álvarez, M.; Rogenhofer, E.; Baraldès-Vallverdú, C.; Lanusse, C.; Salse, N. Food Security Monitoring via Mobile Data Collection and Remote Sensing: Results from the Central African Republic. *PLoS ONE* **2015**, *10*, e0142030. [[CrossRef](#)]
32. Young, H.; Jaspars, S.; Brown, R.; Frize, J.; Khogali, H. *Food-Security Assessments in Emergencies: A Livelihoods Approach*; Overseas Development Institute; Humanitarian Practice Network (HPN): London, UK, 2001.
33. Robinson, A.; Obrecht, A. *Using Mobile Voice Technology to Improve the Collection of Food Security Data: WFP's Mobile Vulnerability Analysis and Mapping' HIF/ALNAP Case Study*; ODI/ALNAP: London, UK, 2016.
34. Henrys, P.A.; Jarvis, S. Integration of ground survey and remote sensing derived data: Producing robust indicators of habitat extent and condition. *Ecol. Evol.* **2019**, *9*, 8104–8112. [[CrossRef](#)]
35. Jayne, T.S.; Rashid, S. The value of accurate crop production forecasts. In *Agricultural Risks Management in Africa: Taking Stock of What Has and Hasn't Worked*; Presented at the Fourth African Agricultural Markets Program (AAMP) Policy Symposium: Lilongwe, Malawi, 2010.
36. Bolton, D.K.; Friedl, M.A. Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics. *Agric. For. Meteorol.* **2013**, *173*, 74–84. [[CrossRef](#)]
37. Stone, R.C.; Meinke, H. Operational seasonal forecasting of crop performance. *Philos. Trans. R. Soc. B Biol. Sci.* **2005**, *360*, 2109–2124. [[CrossRef](#)]
38. Food & Agriculture Organization of the United Nations (FAO). *Global Map of Aridity. Spatial Resolution of 10 Arc Minutes and Temporal Resolution of 1961–1990*; Food and Agriculture Organization of the United Nations (FAO): Rome, Italy, 2009. Available online: <https://data.apps.fao.org/map/catalog/static/api/records/221072ae-2090-48a1-be6f-5a88f061431a> (accessed on 19 August 2020).
39. Qader, S.H.; Dash, J.; Atkinson, P.; Rodriguez-Galiano, V.F. Classification of Vegetation Type in Iraq Using Satellite-Based Phenological Parameters. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2016**, *9*, 414–424. [[CrossRef](#)]
40. Brown, M.E. Satellite Remote Sensing in Agriculture and Food Security Assessment. *Procedia Environ. Sci.* **2015**, *29*, 307. [[CrossRef](#)]
41. Zheng, B.; Myint, S.W.; Thenkabail, P.S.; Aggarwal, R.M. A support vector machine to identify irrigated crop types using time-series Landsat NDVI data. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *34*, 103–112. [[CrossRef](#)]
42. Waldner, F.; De Abelleira, D.; Veron, S.R.; Zhang, M.; Wu, B.F.; Plotnikov, D.; Defourny, P. Towards a set of agrosystem-specific cropland mapping methods to address the global cropland diversity. *Int. J. Remote Sens.* **2016**, *37*, 3196–3231. [[CrossRef](#)]
43. Waldner, F.; Hansen, M.C.; Potapov, P.V.; Low, F.; Newby, T.; Ferreira, S.; Defourny, P. National-scale cropland mapping based on spectral-temporal features and outdated land cover information. *PLoS ONE* **2017**, *12*, e0181911. [[CrossRef](#)]
44. Tong, X.Y.; Brandt, M.; Hiernaux, P.; Herrmann, S.; Rasmussen, L.Y.; Rasmussen, K.; Fensholt, R. The forgotten land use class: Mapping of fallow fields across the Sahel using Sentinel-2. *Remote Sens. Environ.* **2020**, *239*. [[CrossRef](#)]
45. Witmer, F.D.W. Detecting war-induced abandoned agricultural land in northeast Bosnia using multispectral, multitemporal Landsat TM imagery. *Int. J. Remote Sens.* **2008**, *29*, 3805–3831. [[CrossRef](#)]
46. Baumann, M.; Radeloff, V.C.; Avedian, V.; Kuemmerle, T. Land-use change in the Caucasus during and after the Nagorno-Karabakh conflict. *Reg. Environ. Chang.* **2015**, *15*, 1703–1716. [[CrossRef](#)]

47. Ashourloo, D.; Mobasheri, M.R.; Huete, A. Developing Two Spectral Disease Indices for Detection of Wheat Leaf Rust (*Puccinia-tritricina*). *Remote Sens.* **2014**, *6*, 4723–4740. [[CrossRef](#)]
48. Zhang, J.C.; Huang, Y.B.; Yuan, L.; Yang, G.J.; Chen, L.P.; Zhao, C.J. Using satellite multispectral imagery for damage mapping of armyworm (*Spodoptera frugiperda*) in maize at a regional scale. *Pest Manag. Sci.* **2016**, *72*, 335–348. [[CrossRef](#)]
49. Knauer, U.; Matros, A.; Petrovic, T.; Zanker, T.; Scott, E.S.; Seiffert, U. Improved classification accuracy of powdery mildew infection levels of wine grapes by spatial-spectral analysis of hyperspectral images. *Plant Methods* **2017**, *13*. [[CrossRef](#)]
50. Ma, H.Q.; Huang, W.J.; Jing, Y.S.; Yang, C.H.; Han, L.X.; Dong, Y.Y.; Ruan, C. Integrating Growth and Environmental Parameters to Discriminate Powdery Mildew and Aphid of Winter Wheat Using Bi-Temporal Landsat-8 Imagery. *Remote Sens.* **2019**, *11*, 846. [[CrossRef](#)]
51. Bolten, J.D.; Crow, W.; Zhan, X.; Jackson, T.J.; Reynolds, C.A. Evaluating the Utility of Remotely Sensed Soil Moisture Retrievals for Operational Agricultural Drought Monitoring. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2010**, *3*, 57–66. [[CrossRef](#)]
52. Zhang, B.; Di, L.; Yu, G.; Shao, Y.; Shrestha, R.; Kang, L. A Web service based application serving vegetation condition indices for Flood Crop Loss Assessment. In Proceedings of the 2013 Second International Conference on Agro-Geoinformatics (Agro-Geoinformatics), Fairfax, VA, USA, 12–16 August 2013; pp. 215–220.
53. Meroni, M.; Schucknecht, A.; Fasbender, D.; Rembold, F.; Fava, F.; Mauclaire, M.; Goffner, D.; Di Lucchio, L.M.; Leonardi, U. Remote sensing monitoring of land restoration interventions in semi-arid environments with a before–after control-impact statistical design. *Int. J. Appl. Earth Obs. Geoinf.* **2017**, *59*, 42–52. [[CrossRef](#)] [[PubMed](#)]
54. Hunt, M.L.; Blackburn, G.A.; Carrasco, L.; Redhead, J.W.; Rowland, C.S. High resolution wheat yield mapping using Sentinel-2. *Remote Sens. Environ.* **2019**, *233*. [[CrossRef](#)]
55. Burke, M.; Lobell, D.B. Satellite-based assessment of yield variation and its determinants in smallholder African systems. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 2189–2194. [[CrossRef](#)] [[PubMed](#)]
56. Djurfeldt, G.; Hall, O.; Jirstrom, M.; Bustos, M.A.; Holmquist, B.; Nasrin, S. Using panel survey and remote sensing data to explain yield gaps for maize in sub-Saharan Africa. *J. Land Use Sci.* **2018**, *13*, 344–357. [[CrossRef](#)]
57. Jaafar, H.H.; Ahmad, F.A. Crop yield prediction from remotely sensed vegetation indices and primary productivity in arid and semi-arid lands. *Int. J. Remote Sens.* **2015**, *36*, 4570–4589. [[CrossRef](#)]
58. Jaafar, H.H.; Ahmad, F.A. Relationships between primary production and crop yields in semi-arid and arid irrigated agroecosystems. *ISPRS—Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2015**, *XL-7/W3*, 27–30. [[CrossRef](#)]
59. Moumni, A.; Lahrouni, A. Machine Learning-Based Classification for Crop-Type Mapping Using the Fusion of High-Resolution Satellite Imagery in a Semiarid Area. *Scientifica* **2021**, *2021*, 1–20. [[CrossRef](#)]
60. Duncan, J.M.A.; Dash, J.; Atkinson, P. The potential of satellite-observed crop phenology to enhance yield gap assessments in smallholder landscapes. *Front. Environ. Sci.* **2015**, *3*, 2547. [[CrossRef](#)]
61. Suepa, T.; Qi, J.; Lawawirojwong, S.; Messina, J. Understanding spatio-temporal variation of vegetation phenology and rainfall seasonality in the monsoon Southeast Asia. *Environ. Res.* **2016**, *147*, 621–629. [[CrossRef](#)] [[PubMed](#)]
62. Adole, T.; Dash, J.; Atkinson, P.M. Characterising the land surface phenology of Africa using 500 m MODIS EVI. *Appl. Geogr.* **2018**, *90*, 187–199. [[CrossRef](#)]
63. Fritz, S.; See, L. Identifying and quantifying uncertainty and spatial disagreement in the comparison of Global Land Cover for different applications. *Glob. Chang. Biol.* **2008**, *14*, 1057–1075. [[CrossRef](#)]
64. Friedl, M.A.; Sulla-Menashe, D.; Tan, B.; Schneider, A.; Ramankutty, N.; Sibley, A.; Huang, X. MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sens. Environ.* **2010**, *114*, 168–182. [[CrossRef](#)]
65. Singh, N.; Glenn, N.F. Multitemporal spectral analysis for cheatgrass (*Bromus tectorum*) classification. *Int. J. Remote Sens.* **2009**, *30*, 3441–3462. [[CrossRef](#)]
66. Key, T.; Warner, T.A.; McGraw, J.B.; Fajvan, M.A. Comparison of Multispectral and Multitemporal Information in High Spatial Resolution Imagery for Classification of Individual Tree Species in a Temperate Hardwood Forest. *Remote Sens. Environ.* **2001**, *75*, 100–112. [[CrossRef](#)]
67. Song, C.; Woodcock, C. Monitoring forest succession with multitemporal landsat images: Factors of uncertainty. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 2557–2567. [[CrossRef](#)]
68. Pal, M.; Mather, P.M. Support vector machines for classification in remote sensing. *Int. J. Remote Sens.* **2005**, *26*, 1007–1011. [[CrossRef](#)]
69. Ham, J.; Chen, Y.; Crawford, M.; Ghosh, J. Investigation of the random forest framework for classification of hyperspectral data. *IEEE Trans. Geosci. Remote Sens.* **2005**, *43*, 492–501. [[CrossRef](#)]
70. Heupel, K.; Spengler, D.; Itzerott, S. A Progressive Crop-Type Classification Using Multitemporal Remote Sensing Data and Phenological Information. *PFG—J. Photogramm. Remote Sens. Geoinf. Sci.* **2018**, *86*, 53–69. [[CrossRef](#)]
71. Carfagna, E.; Gallego, F.J. Using Remote Sensing for Agricultural Statistics. *International Statistical Review/Revue Internationale De Statistique*. 2005; pp. 389–404. Available online: www.jstor.org/stable/25472682 (accessed on 16 August 2021).
72. Moumni, A.; Oujaoura, M.; Ezzahar, J.; Lahrouni, A. A new synergistic approach for crop discrimination in a semi-arid region using Sentinel-2 time series and the multiple combination of machine learning classifiers. *J. Physics Conf. Ser.* **2021**, *1743*, 012026. [[CrossRef](#)]
73. Rufin, P.; Frantz, D.; Ernst, S.; Rabe, A.; Griffiths, P.; Özdoğan, M.; Hostert, P. Mapping Cropping Practices on a National Scale Using Intra-Annual Landsat Time Series Binning. *Remote Sens.* **2019**, *11*, 232. [[CrossRef](#)]

74. Ennouri, K.; Kallel, A. Remote Sensing: An Advanced Technique for Crop Condition Assessment. *Math. Probl. Eng.* **2019**, *2019*, 9404565. [[CrossRef](#)]
75. Wang, L.; Tian, Y.; Yao, X.; Zhu, Y.; Cao, W. Predicting grain yield and protein content in wheat by fusing multi-sensor and multi-temporal remote-sensing images. *Field Crops Res.* **2014**, *164*, 178–188. [[CrossRef](#)]
76. Steensland, A. 2020 Global Agricultural Productivity Report: Productivity in a time of pandemics. 2020. Available online: <https://vtechworks.lib.vt.edu/handle/10919/102008> (accessed on 16 August 2021).
77. Del Rio, A.; Simpson, B.M. *Agricultural Adaptation to Climate Change in the Sahel: Expected Impacts on Pests and Diseases Afflicting Selected Crops*; USAID: Washington, DC, USA, 2014.
78. Hemmati, C.; Nikooei, M.; Al-Subhi, A.; Al-Sadi, A. History and Current Status of Phytoplasma Diseases in the Middle East. *Biology* **2021**, *10*, 226. [[CrossRef](#)]
79. Meyer, M.; Cox, J.A.; Hitchings, M.D.T.; Burgin, L.; Hort, M.C.; Hodson, D.P.; Gilligan, C.A. Quantifying airborne dispersal routes of pathogens over continents to safeguard global wheat supply. *Nat. Plants* **2017**, *3*, 780–786. [[CrossRef](#)] [[PubMed](#)]
80. United States Department of Agriculture Foreign Agricultural Service (USDA FAS). MIDDLE EAST: Yellow Rust Epidemic Affects Regional Wheat Crops. 2010. Available online: <https://ipad.fas.usda.gov/highlights/2010/06/Middle%20East/> (accessed on 13 May 2021).
81. Simons, S. Management strategies for maize grey leaf spot (*Cercospora zeae-maydis*) in Kenya and Zimbabwe. *DFID Tech. Rep.* **2006**, *R7566*, 1–67.
82. Oerke, E.C. Crop losses to pests. *J. Agric. Sci.* **2006**, *144*, 31–43. [[CrossRef](#)]
83. Hruska, A. Fall armyworm (Spodoptera frugiperda) management by smallholders. *CAB Rev.* **2019**, *14*, 1–11. [[CrossRef](#)]
84. Kasoma, C.; Shimelis, H.; Laing, M.D. Fall armyworm invasion in Africa: Implications for maize production and breeding. *J. Crop Improv.* **2021**, *35*, 111–146. [[CrossRef](#)]
85. Lesk, C.; Rowhani, P.; Ramankutty, N. Influence of extreme weather disasters on global crop production. *Nature* **2016**, *529*, 84. [[CrossRef](#)]
86. Singh, N.P.; Bantilan, C.; Byjesh, K. Vulnerability and policy relevance to drought in the semi-arid tropics of Asia—A retrospective analysis. *Weather. Clim. Extremes* **2014**, *3*, 54–61. [[CrossRef](#)]
87. Kamali, B.; Abbaspour, K.C.; Lehmann, A.; Wehrli, B.; Yang, H. Spatial assessment of maize physical drought vulnerability in sub-Saharan Africa: Linking drought exposure with crop failure. *Environ. Res. Lett.* **2018**, *13*, 074010. [[CrossRef](#)]
88. Erian, W.; Katlan, B.; Assad, N.; Ibrahim, S. *Effects of Drought and Land Degradation on Vegetation Losses in Africa, Arab Region with Special Case Study on: Drought and Conflict in Syria, South America and Forests of Amazon and Congo Rivers Basins*; Background Paper Prepared for the 2015 Global Assessment Report on Disaster Risk Reduction; UNISDR: Geneva, Switzerland, 2014.
89. Barlow, M.; Zaitchik, B.; Paz, S.; Black, E.; Evans, J.; Hoell, A. A Review of Drought in the Middle East and Southwest Asia. *J. Clim.* **2016**, *29*, 8547–8574. [[CrossRef](#)]
90. Kandeel, A.A. In the Face of Climate Change: Challenges of Water Scarcity and Security in MENA. 11 June 2019. Atlantic Council. Available online: <https://www.atlanticcouncil.org/blogs/menasource/in-the-face-of-climate-change-challenges-of-water-scarcity-and-security-in-mena/> (accessed on 17 March 2021).
91. United States Department of Agriculture Foreign Agricultural Service (USDA FAS). Drought Reduces 2008/09 Winter Grain Yield, USDA-FAS, Office of Global Analysis. 2008. Available online: http://www.pecad.fas.usda.gov/highlights/2008/05/iraq_may2008.htm (accessed on 16 November 2020).
92. Sultan, B.; Defrance, D.; Iizumi, T. Evidence of crop production losses in West Africa due to historical global warming in two crop models. *Sci. Rep.* **2019**, *9*, 1–15. [[CrossRef](#)] [[PubMed](#)]
93. Meng, J.-H.; Wu, B.-F. Study on the crop condition monitoring methods with remote sensing. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2008**, *37*, 945–950.
94. Cogato, A.; Meggio, F.; Migliorati, M.D.; Marinello, F. Extreme Weather Events in Agriculture: A Systematic Review. *Sustainability* **2019**, *11*, 2547. [[CrossRef](#)]
95. Sazib, N.; Mladenova, L.E.; Bolten, J.D. Assessing the Impact of ENSO on Agriculture Over Africa Using Earth Observation Data. *Front. Sustain. Food Syst.* **2020**, *4*, 188. [[CrossRef](#)]
96. Mechiche-Alami, A.; Abdi, A.M. Agricultural productivity in relation to climate and cropland management in West Africa. *Sci. Rep.* **2020**, *10*, 1–10. [[CrossRef](#)]
97. Sankaran, S.; Mishra, A.; Ehsani, R.; Davis, C. A review of advanced techniques for detecting plant diseases. *Comput. Electron. Agric.* **2010**, *72*, 1–13. [[CrossRef](#)]
98. Yuan, L.; Zhang, H.; Zhang, Y.; Xing, C.; Bao, Z. Feasibility assessment of multi-spectral satellite sensors in monitoring and discriminating wheat diseases and insects. *Optik* **2017**, *131*, 598–608. [[CrossRef](#)]
99. Raikes, C.; Burpee, L.L. Use of multispectral radiometry for assessment of rhizoctonia blight in creeping bentgrass. *Phytopathology* **1998**, *88*, 446–449. [[CrossRef](#)]
100. Chen, X.; Ma, J.; Qiao, H.; Cheng, D.; Xu, Y.; Zhao, Y. Detecting infestation of take-all disease in wheat using Land-sat Thematic Mapper imagery. *Int. J. Remote Sens.* **2007**, *28*, 5183–5189. [[CrossRef](#)]
101. Piou, C.; Gay, P.E.; Benahi, A.S.; Ebbe, M.; Chihrane, J.; Ghaout, S.; Escorihuela, M.J. Soil moisture from remote sensing to forecast desert locust presence. *J. Appl. Ecol.* **2019**, *56*, 966–975. [[CrossRef](#)]

102. Krishna, T.M.; Ravikumar, G.; Krishnaveni, M. Remote Sensing Based Agricultural Drought Assessment in Palar Basin of Tamil Nadu State, India. *J. Indian Soc. Remote Sens.* **2009**, *37*, 9–20. [[CrossRef](#)]
103. Rembold, F.; Meroni, M.; Urbano, F.; Lemoine, G.; Kerdiles, H.; Perez-Hoyos, A. ASAP-Anomaly hot Spots of Agricultural Production, a new early warning decision support system developed by the Joint Research Centre. In Proceedings of the 2017 9th International Workshop on the Analysis of Multitemporal Remote Sensing Images (MultiTemp), Bruges, Belgium, 27–29 June 2017.
104. Kahan, D. *Managing Risk in Farming*; Food and agriculture organization of the United Nations: Rome, Italy, 2008.
105. Pease, J.W.; Wade, E.W.; Skees, J.S.; Shrestha, C.M. Comparisons between Subjective and Statistical Forecasts of Crop Yields. *Rev. Agric. Econ.* **1993**, *15*, 339–350. [[CrossRef](#)]
106. Qian, B.; De Jong, R.; Warren, R.; Chipanshi, A.; Hill, H. Statistical spring wheat yield forecasting for the Canadian prairie provinces. *Agric. For. Meteorol.* **2009**, *149*, 1022–1031. [[CrossRef](#)]
107. Raja, R.; Nayak, A.; Panda, B.; Lal, B.; Tripathi, R.; Shahid, M.; Kumar, A.; Mohanty, S.; Samal, P.; Gautam, P.; et al. Monitoring of meteorological drought and its impact on rice (*Oryza sativa* L.) productivity in Odisha using standardized precipitation index. *Arch. Agron. Soil Sci.* **2014**, *60*, 1701–1715. [[CrossRef](#)]
108. Basso, B.; Liu, L. Seasonal crop yield forecast: Methods, applications, and accuracies. In *Advances in Agronomy*; Sparks, D.L., Ed.; 2019; Volume 154, pp. 201–255. Available online: https://www.academia.edu/41108597/Seasonal_crop_yield_forecast_Methods_applications_and_accuracies (accessed on 16 August 2021).
109. Battude, M.; Al Bitar, A.; Morin, D.; Cros, J.; Huc, M.; Sicre, C.M.; Le Dantec, V.; Demarez, V. Estimating maize biomass and yield over large areas using high spatial and temporal resolution Sentinel-2 like remote sensing data. *Remote Sens. Environ.* **2016**, *184*, 668–681. [[CrossRef](#)]
110. Ban, H.-Y.; Kim, K.S.; Park, N.-W.; Lee, B.-W. Using MODIS Data to Predict Regional Corn Yields. *Remote Sens.* **2017**, *9*, 16. [[CrossRef](#)]
111. Basso, B.; Liu, L.; Ritchie, J.T. A Comprehensive Review of the CERES-Wheat, -Maize and -Rice Models' Performances. *Adv. Agron.* **2016**, *136*, 27–132.
112. Basso, B.; Cammarano, D.; Carfagna, E. Review of Crop Yield Forecasting Methods and Early Warning Systems. In *Proceedings of the First Meeting of the Scientific Advisory Committee of the Global Strategy to Improve Agricultural and Rural Statistics*; FAO Headquarters: Rome, Italy, 2013; pp. 1–56. Available online: http://www.fao.org/fileadmin/templates/ess/documents/meetings_and_workshops/GS_SAC_2013/Improving_methods_for_crops_estimates/Crop_Yield_Forecasting_Methods_and_Early_Warning_Systems_Lit_review.pdf (accessed on 11 June 2021).
113. Hielkema, J.; Snijders, F. Operational use of environmental satellite remote sensing and satellite communications technology for global food security and locust control by FAO: The ARTEMIS and DIANA systems. *Acta Astronaut.* **1994**, *32*, 603–616. [[CrossRef](#)]
114. Chahbi, A.; Zribi, M.; Lili-Chabaane, Z.; Duchemin, B.; Shabou, M.; Mougénot, B.; Boulet, G. Estimation of the dynamics and yields of cereals in a semi-arid area using remote sensing and the SAFY growth model. *Int. J. Remote Sens.* **2014**, *35*, 1004–1028. [[CrossRef](#)]
115. Ahmad, I.; Singh, A.; Fahad, M.; Waqas, M.M. Remote sensing-based framework to predict and assess the interannual variability of maize yields in Pakistan using Landsat imagery. *Comput. Electron. Agric.* **2020**, *178*, 105732. [[CrossRef](#)]
116. Peng, B.; Guan, K.; Zhou, W.; Jiang, C.; Frankenberg, C.; Sun, Y.; He, L.; Köhler, P. Assessing the benefit of satellite-based Solar-Induced Chlorophyll Fluorescence in crop yield prediction. *Int. J. Appl. Earth Obs. Geoinf.* **2020**, *90*, 102126. [[CrossRef](#)]
117. Schwalbert, R.A.; Amado, T.; Corassa, G.; Pott, L.P.; Prasad, P.; Ciampitti, I.A. Satellite-based soybean yield forecast: Integrating machine learning and weather data for improving crop yield prediction in southern Brazil. *Agric. For. Meteorol.* **2020**, *284*, 107886. [[CrossRef](#)]
118. Abbas, F.; Afzaal, H.; Farooque, A.A.; Tang, S. Crop Yield Prediction through Proximal Sensing and Machine Learning Algorithms. *Agronomy* **2020**, *10*, 1046. [[CrossRef](#)]
119. Han, J.; Zhang, Z.; Cao, J.; Luo, Y.; Zhang, L.; Li, Z.; Zhang, J. Prediction of Winter Wheat Yield Based on Multi-Source Data and Machine Learning in China. *Remote Sens.* **2020**, *12*, 236. [[CrossRef](#)]
120. Sharifi, A. Yield prediction with machine learning algorithms and satellite images. *J. Sci. Food Agric.* **2021**, *101*, 891–896. [[CrossRef](#)] [[PubMed](#)]
121. Stepanov, A.; Dubrovin, K.; Sorokin, A.; Aseeva, T. Predicting Soybean Yield at the Regional Scale Using Remote Sensing and Climatic Data. *Remote Sens.* **2020**, *12*, 1936. [[CrossRef](#)]
122. Leroux, L.; Falconnier, G.; Diouf, A.; Ndao, B.; Gbodjo, Y.J.E.; Tall, L.; Balde, A.; Clermont-Dauphin, C.; Bégué, A.; Affholder, F.; et al. Using remote sensing to assess the effect of trees on millet yield in complex parklands of Central Senegal. *Agric. Syst.* **2020**, *184*, 102918. [[CrossRef](#)]
123. Feng, L.; Zhang, Z.; Ma, Y.; Du, Q.; Williams, P.; Drewry, J.; Luck, B. Alfalfa Yield Prediction Using UAV-Based Hyperspectral Imagery and Ensemble Learning. *Remote Sens.* **2020**, *12*, 2028. [[CrossRef](#)]
124. Rahman, M.M.; Robson, A. Integrating Landsat-8 and Sentinel-2 Time Series Data for Yield Prediction of Sugarcane Crops at the Block Level. *Remote Sens.* **2020**, *12*, 1313. [[CrossRef](#)]
125. Zhao, Y.; Potgieter, A.B.; Zhang, M.; Wu, B.; Hammer, G.L. Predicting Wheat Yield at the Field Scale by Combining High-Resolution Sentinel-2 Satellite Imagery and Crop Modelling. *Remote Sens.* **2020**, *12*, 1024. [[CrossRef](#)]

126. Wang, X.; Huang, J.; Feng, Q.; Yin, D. Winter Wheat Yield Prediction at County Level and Uncertainty Analysis in Main Wheat-Producing Regions of China with Deep Learning Approaches. *Remote Sens.* **2020**, *12*, 1744. [[CrossRef](#)]
127. Gaso, D.V.; Berger, A.G.; Ciganda, V.S. Predicting wheat grain yield and spatial variability at field scale using a simple regression or a crop model in conjunction with Landsat images. *Comput. Electron. Agric.* **2019**, *159*, 75–83. [[CrossRef](#)]
128. Chen, Y.; Lee, W.S.; Gan, H.; Peres, N.; Fraisse, C.; Zhang, Y.; He, Y. Strawberry yield prediction based on a deep neural network using high-resolution aerial orthoimages. *Remote Sens.* **2019**, *11*, 1584. [[CrossRef](#)]
129. Kang, Y.; Özdoğan, M. Field-level crop yield mapping with Landsat using a hierarchical data assimilation approach. *Remote Sens. Environ.* **2019**, *228*, 144–163. [[CrossRef](#)]
130. Peng, Y.; Zhu, T.; Li, Y.; Dai, C.; Fang, S.; Gong, Y.; Wu, X.; Zhu, R.; Liu, K. Remote prediction of yield based on LAI estimation in oilseed rape under different planting methods and nitrogen fertilizer applications. *Agric. For. Meteorol.* **2019**, *271*, 116–125. [[CrossRef](#)]
131. Xu, J.; Meng, J.; Quackenbush, L.J. Use of remote sensing to predict the optimal harvest date of corn. *Field Crops Res.* **2019**, *236*, 1–13. [[CrossRef](#)]
132. Donohue, R.J.; Lawes, R.; Mata, G.; Gobbett, D.; Ouzman, J. Towards a national, remote-sensing-based model for predicting field-scale crop yield. *Field Crops Res.* **2018**, *227*, 79–90. [[CrossRef](#)]
133. Peng, B.; Guan, K.; Pan, M.; Li, Y. Benefits of Seasonal Climate Prediction and Satellite Data for Forecasting U.S. Maize Yield. *Geophys. Res. Lett.* **2018**, *45*, 9662–9671. [[CrossRef](#)]
134. Kanning, M.; Kühling, I.; Trautz, D.; Jarmer, T. High-Resolution UAV-Based Hyperspectral Imagery for LAI and Chlorophyll Estimations from Wheat for Yield Prediction. *Remote Sens.* **2018**, *10*, 2000. [[CrossRef](#)]
135. Chen, Y.; Zhang, Z.; Tao, F. Improving regional winter wheat yield estimation through assimilation of phenology and leaf area index from remote sensing data. *Eur. J. Agron.* **2018**, *101*, 163–173. [[CrossRef](#)]
136. Khanal, S.; Fulton, J.; Klopfenstein, A.; Douridas, N.; Shearer, S. Integration of high resolution remotely sensed data and machine learning techniques for spatial prediction of soil properties and corn yield. *Comput. Electron. Agric.* **2018**, *153*, 213–225. [[CrossRef](#)]
137. Gao, F.; Anderson, M.; Daughtry, C.; Johnson, D. Assessing the Variability of Corn and Soybean Yields in Central Iowa Using High Spatiotemporal Resolution Multi-Satellite Imagery. *Remote Sens.* **2018**, *10*, 1489. [[CrossRef](#)]
138. Haghverdi, A.; Washington-Allen, R.A.; Leib, B.G. Prediction of cotton lint yield from phenology of crop indices using artificial neural networks. *Comput. Electron. Agric.* **2018**, *152*, 186–197. [[CrossRef](#)]
139. Guo, C.; Zhang, L.; Zhou, X.; Zhu, Y.; Cao, W.; Qiu, X.; Cheng, T.; Tian, Y. Integrating remote sensing information with crop model to monitor wheat growth and yield based on simulation zone partitioning. *Precis. Agric.* **2018**, *19*, 55–78. [[CrossRef](#)]
140. Rahman, M.M.; Robson, A.; Bristow, M. Exploring the potential of high resolution worldview-3 Imagery for estimating yield of mango. *Remote Sens.* **2018**, *10*, 1866. [[CrossRef](#)]
141. Kern, A.; Barcza, Z.; Marjanović, H.; Árendás, T.; Fodor, N.; Bónis, P.; Bognár, P.; Lichtenberger, J. Statistical modelling of crop yield in Central Europe using climate data and remote sensing vegetation indices. *Agric. For. Meteorol.* **2018**, *260–261*, 300–320. [[CrossRef](#)]
142. Sanches, G.M.; Duft, D.G.; Kölln, O.; Luciano, A.C.D.S.; De Castro, S.G.Q.; Okuno, F.M.; Franco, H.C.J. The potential for RGB images obtained using unmanned aerial vehicle to assess and predict yield in sugarcane fields. *Int. J. Remote Sens.* **2018**, *39*, 5402–5414. [[CrossRef](#)]
143. Lai, Y.; Pringle, M.; Kopittke, P.; Menzies, N.; Orton, T.; Dang, Y. An empirical model for prediction of wheat yield, using time-integrated Landsat NDVI. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *72*, 99–108. [[CrossRef](#)]
144. Kawamura, K.; Ikeura, H.; Phongchanmaixay, S.; Khanthavong, P. Canopy Hyperspectral Sensing of Paddy Fields at the Booting Stage and PLS Regression can Assess Grain Yield. *Remote Sens.* **2018**, *10*, 1249. [[CrossRef](#)]
145. Newton, I.H.; Islam, A.F.M.T.; Islam, A.K.M.S.; Islam, G.M.T.; Tahsin, A.; Razzaque, S. Yield Prediction Model for Potato Using Landsat Time Series Images Driven Vegetation Indices. *Remote Sens. Earth Syst. Sci.* **2018**, *1*, 29–38. [[CrossRef](#)]
146. Zhou, X.; Zheng, H.; Xu, X.; He, J.; Ge, X.; Yao, X.; Cheng, T.; Zhu, Y.; Cao, W.; Tian, Y. Predicting grain yield in rice using multi-temporal vegetation indices from UAV-based multispectral and digital imagery. *ISPRS J. Photogramm. Remote Sens.* **2017**, *130*, 246–255. [[CrossRef](#)]
147. Sun, L.; Gao, F.; Anderson, M.C.; Kustas, W.P.; Alsina, M.M.; Sanchez, L.; Sams, B.; McKee, L.; Dulaney, W.; White, W.A.; et al. Daily Mapping of 30 m LAI and NDVI for Grape Yield Prediction in California Vineyards. *Remote Sens.* **2017**, *9*, 317. [[CrossRef](#)]
148. Jin, X.; Li, Z.; Yang, G.; Yang, H.; Feng, H.; Xu, X.; Wang, J.; Li, X.; Luo, J. Winter wheat yield estimation based on multi-source medium resolution optical and radar imaging data and the AquaCrop model using the particle swarm optimization algorithm. *ISPRS J. Photogramm. Remote Sens.* **2017**, *126*, 24–37. [[CrossRef](#)]
149. Fernandes, J.L.; Ebecken, N.F.F.; Esquerdo, J. Sugarcane yield prediction in Brazil using NDVI time series and neural networks ensemble. *Int. J. Remote Sens.* **2017**, *38*, 4631–4644. [[CrossRef](#)]
150. Shrestha, R.; Di, L.; Yu, E.G.; Kang, L.; Shao, Y.-Z.; Bai, Y.-Q. Regression model to estimate flood impact on corn yield using MODIS NDVI and USDA cropland data layer. *J. Integr. Agric.* **2017**, *16*, 398–407. [[CrossRef](#)]
151. Jain, M.; Srivastava, A.K.; Balwinder-Singh; Joon, R.K.; McDonald, A.; Royal, K.; Lisaius, M.C.; Lobell, D.B. Mapping Smallholder Wheat Yields and Sowing Dates Using Micro-Satellite Data. *Remote Sens.* **2016**, *8*, 860. [[CrossRef](#)]
152. Maresma, Á.; Ariza, M.; Martínez, E.; Lloveras, J.; Martínez-Casasnovas, J.A. Analysis of vegetation indices to determine nitrogen application and yield prediction in maize (*Zea mays* L.) from a standard UAV service. *Remote Sens.* **2016**, *8*, 973. [[CrossRef](#)]

153. Al-Gaadi, K.A.; Hassaballa, A.; Tola, E.; Kayad, A.; Madugundu, R.; Alblewi, B.; Assiri, F. Prediction of Potato Crop Yield Using Precision Agriculture Techniques. *PLoS ONE* **2016**, *11*, e0162219. [[CrossRef](#)]
154. Vergara-Díaz, O.; Zaman-Allah, M.A.; Masuka, B.; Hornero, A.; Zarco-Tejada, P.; Prasanna, B.M.; Araus, J.L. A novel remote sensing approach for prediction of maize yield under different conditions of nitrogen fertilization. *Front. Plant Sci.* **2016**, *7*, 666. [[CrossRef](#)]
155. Satir, O.; Berberoglu, S. Crop yield prediction under soil salinity using satellite derived vegetation indices. *Field Crops Res.* **2016**, *192*, 134–143. [[CrossRef](#)]
156. Yao, F.; Tang, Y.; Wang, P.; Zhang, J. Estimation of maize yield by using a process-based model and remote sensing data in the Northeast China Plain. *Phys. Chem. Earth Parts A/B/C* **2015**, *87–88*, 142–152. [[CrossRef](#)]
157. Kuwata, K.; Shibasaki, R. Estimating crop yields with deep learning and remotely sensed data. In Proceedings of the 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Milan, Italy, 26–31 July 2015; pp. 858–861.
158. Siyal, A.A.; Dempewolf, J.; Becker-Reshef, I. Rice yield estimation using Landsat ETM + Data. *J. Appl. Remote Sens.* **2015**, *9*, 095986. [[CrossRef](#)]
159. Heremans, S.; Dong, Q.; Zhang, B.; Bydekerke, L.; Van Orshoven, J. Potential of ensemble tree methods for early-season prediction of winter wheat yield from short time series of remotely sensed normalized difference vegetation index and in situ meteorological data. *J. Appl. Remote Sens.* **2015**, *9*, 097095. [[CrossRef](#)]
160. Sakamoto, T.; Gitelson, A.A.; Arkebauer, T.J. Near real-time prediction of U.S. corn yields based on time-series MODIS data. *Remote Sens. Environ.* **2014**, *147*, 219–231. [[CrossRef](#)]
161. Batini, C.; Blaschke, T.; Lang, S.; Albrecht, F.; Abdulmutalib, H.M.; Barsi, Á.; Szabó, G.; Kugler, Z.s. Data Quality in Remote Sensing. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.* **2017**, *XLII-2/W7*, 447–453. [[CrossRef](#)]
162. Reynolds, C.A.; Yitayew, M.; Slack, D.C.; Hutchinson, C.F.; Huete, A.; Petersen, M.S. Estimating crop yields and production by integrating the FAO Crop Specific Water Balance model with real-time satellite data and ground-based ancillary data. *Int. J. Remote Sens.* **2000**, *21*, 3487–3508. [[CrossRef](#)]
163. Carletto, C.; Jolliffe, D.; Banerjee, R. *The Emperor Has No Data! Agricultural Statistics in Sub-Saharan Africa*; World Bank Working Paper; World Bank: Washington, DC, USA, 2013.
164. Paliwal, A.; Jain, M. The Accuracy of Self-Reported Crop Yield Estimates and Their Ability to Train Remote Sensing Algorithms. *Front. Sustain. Food Syst.* **2020**, *4*, 25. [[CrossRef](#)]
165. Bruzzone, L.; Persello, C. A Novel Context-Sensitive Semisupervised SVM Classifier Robust to Mislabeled Training Samples. *IEEE Trans. Geosci. Remote Sens.* **2009**, *47*, 2142–2154. [[CrossRef](#)]
166. Mellor, A.; Boukir, S.; Haywood, A.; Jones, S. Exploring issues of training data imbalance and mislabelling on random forest performance for large area land cover classification using the ensemble margin. *ISPRS J. Photogramm. Remote Sens.* **2015**, *105*, 155–168. [[CrossRef](#)]
167. Foody, G.M.; Pal, M.; Rocchini, D.; Garzon-Lopez, C.X.; Bastin, L. The Sensitivity of Mapping Methods to Reference Data Quality: Training Supervised Image Classifications with Imperfect Reference Data. *ISPRS Int. J. Geoinf.* **2016**, *5*, 199. [[CrossRef](#)]
168. Scott, W.A.; Hallam, C.J. Assessing species misidentification rates through quality assurance of vegetation monitoring. *Plant Ecol.* **2003**, *165*, 101–115. [[CrossRef](#)]
169. Costa, H.; Foody, G.M.; Jiménez, S.; Silva, L. Impacts of Species Misidentification on Species Distribution Modeling with Presence-Only Data. *ISPRS Int. J. Geoinf.* **2015**, *4*, 2496–2518. [[CrossRef](#)]
170. Wu, H.; Li, Z.-L. Scale Issues in Remote Sensing: A Review on Analysis, Processing and Modeling. *Sensors* **2009**, *9*, 1768–1793. [[CrossRef](#)]
171. Shao, Y.; Dong, C. A review on East Asian dust storm climate, modelling and monitoring. *Glob. Planet. Chang.* **2006**, *52*, 1–22. [[CrossRef](#)]
172. Houborg, R.; McCabe, M. Impacts of dust aerosol and adjacency effects on the accuracy of Landsat 8 and RapidEye surface reflectances. *Remote Sens. Environ.* **2017**, *194*, 127–145. [[CrossRef](#)]
173. Baret, F.; Buis, S. Estimating Canopy Characteristics from Remote Sensing Observations: Review of Methods and Associated Problems. In *Advances in Land Remote Sensing: System, Modeling, Inversion and Application*; Liang, S., Ed.; Springer: Dordrecht, The Netherlands, 2008; pp. 173–201.
174. Chaabouni, S.; Kallel, A.; Houborg, R. Improving retrieval of crop biophysical properties in dryland areas using a multi-scale variational RTM inversion approach. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *94*, 102220. [[CrossRef](#)]
175. Berk, A.; Anderson, G.P.; Bernstein, L.S.; Acharya, P.K.; Dothe, H.; Matthew, M.W.; Adler-Golden, S.M.; Chetwynd, J.J.H.; Richtsmeier, S.C.; Pukall, B.; et al. MODTRAN4 radiative transfer modeling for atmospheric correction. *SPIE's Int. Symp. Opt. Sci. Eng. Instrum.* **1999**, *3756*, 348. [[CrossRef](#)]
176. Vermote, E.F.; Saleous, N. Operational Atmospheric Correction of MODIS Visible to Middle Infrared Land Surface Data in the Case of an Infinite Lambertian Target. In *Earth Science Satellite Remote Sensing*; Springer: Berlin/Heidelberg, Germany, 2007; pp. 123–153.
177. Dinter, T.; Von Hoyningen-Huene, W.; Burrows, J.P.; Kokhanovsky, A.; Bierwirth, E.; Wendisch, M.; Mueller, D.; Kahn, R.; Diouri, M. Retrieval of aerosol optical thickness for desert conditions using MERIS observations during the SAMUM campaign. *Tellus B Chem. Phys. Meteorol.* **2009**, *61*, 229–238. [[CrossRef](#)]

178. Kahn, R.A.; Gaitley, B.J.; Garay, M.J.; Diner, D.J.; Eck, T.F.; Smirnov, A.; Holben, B.N. Multiangle Imaging Spectroradiometer global aerosol product assessment by comparison with the Aerosol Robotic Network. *J. Geophys. Res. Space Phys.* **2010**, *115*, 1–28. [[CrossRef](#)]
179. Sayer, A.; Munchak, L.A.; Hsu, N.C.; Levy, R.; Bettenhausen, C.; Jeong, M.J. MODIS Collection 6 aerosol products: Comparison between Aqua's e-Deep Blue, Dark Target, and "merged" data sets, and usage recommendations. *J. Geophys. Res. Atmos.* **2014**, *119*, 13965–13989. [[CrossRef](#)]
180. Dubovik, O.; Herman, M.; Holdak, A.; Lapyonok, T.; Tanré, D.; Deuzé, J.L.; Ducos, F.; Sinyuk, A.; Lopatin, A. Statistically optimized inversion algorithm for enhanced retrieval of aerosol properties from spectral multi-angle polarimetric satellite observations. *Atmos. Meas. Tech.* **2011**, *4*, 975–1018. [[CrossRef](#)]
181. Sayer, A.M.; Hsu, N.C.; Bettenhausen, C.; Jeong, M.; Meister, G. Effect of MODIS Terra radiometric calibration improvements on Collection 6 Deep Blue aerosol products: Validation and Terra/Aqua consistency. *J. Geophys. Res. Atmos.* **2015**, *120*, 12157–12174. [[CrossRef](#)]
182. Masek, J.G.; Vermote, E.F.; Saleous, N.E.; Wolfe, R.; Hall, F.G.; Huemmrich, K.F.; Lim, T.K. A Landsat surface reflectance dataset for North America, 1990–2000. *IEEE Geosci. Remote Sens. Lett.* **2006**, *3*, 68–72. [[CrossRef](#)]
183. Xue, J.; Su, B. Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *J. Sens.* **2017**, *2017*, 1353691. [[CrossRef](#)]
184. Okin, G.S.; Roberts, D.A. Remote sensing in arid regions: Challenges and opportunities. In *Manual of Remote Sensing*; Ustin, S., Ed.; John Wiley & Sons: New York, NY, USA, 2004; pp. 111–146.
185. Gamo, M.; Shinoda, M.; Maeda, T. Classification of arid lands, including soil degradation and irrigated areas, based on vegetation and aridity indices. *Int. J. Remote Sens.* **2013**, *34*, 6701–6722. [[CrossRef](#)]
186. Escadafal, R.; Huete, A. Improvement in Remote-Sensing of Low Vegetation Cover in Arid Regions by Correcting Vegetation Indexes for Soil Noise. *C. R. L'Acad. Sci. Ser. 2 Mec. Phys. Chim. Sci. L'Univ. Sci. Terre* **1991**, *312*, 1385–1391.
187. Huete, A.; Tucker, C.J. Investigation of soil influences in AVHRR red and near-infrared vegetation index imagery. *Int. J. Remote Sens.* **1991**, *12*, 1223–1242. [[CrossRef](#)]
188. Guerschman, J.; Scarth, P.; McVicar, T.; Renzullo, L.J.; Malthus, T.; Stewart, J.B.; Rickards, J.E.; Trevithick, R. Assessing the effects of site heterogeneity and soil properties when unmixing photosynthetic vegetation, non-photosynthetic vegetation and bare soil fractions from Landsat and MODIS data. *Remote Sens. Environ.* **2015**, *161*, 12–26. [[CrossRef](#)]
189. Dawelbait, M.; Morari, F. Limits and Potentialities of Studying Dryland Vegetation Using the Optical Remote Sensing. *Ital. J. Agron.* **2008**, *3*, 97–106. [[CrossRef](#)]
190. Tongway, D.J.; Ludwig, J.A. Heterogeneity in arid and semiarid lands (Chapter 10). In *Ecosystem Function in Heterogeneous Landscapes*; Lovett, G.M., Turner, M.G., Jones, C.G., Weathers, K.C., Eds.; Springer: New York, NY, USA, 2005; pp. 189–205.
191. Tan, B.; Woodcock, C.; Hu, J.; Zhang, P.; Ozdogan, M.; Huang, D.; Yang, W.; Knyazikhin, Y.; Myneni, R. The impact of gridding artifacts on the local spatial properties of MODIS data: Implications for validation, compositing, and band-to-band registration across resolutions. *Remote Sens. Environ.* **2006**, *105*, 98–114. [[CrossRef](#)]
192. Gómez-Chova, L.; Zurita-Milla, R.; Alonso, L.; Amorós-López, J.; Guanter, L.; Camps-Valls, G. Gridding Artifacts on Medium-Resolution Satellite Image Time Series: MERIS Case Study. *IEEE Trans. Geosci. Remote Sens.* **2011**, *49*, 2601–2611. [[CrossRef](#)]
193. Delrue, J.; Bydekerke, L.; Eerens, H.; Gilliams, S.; Piccard, I.; Swinnen, E. Crop mapping in countries with small-scale farming: A case study for West Shewa, Ethiopia. *Int. J. Remote Sens.* **2012**, *34*, 2566–2582. [[CrossRef](#)]
194. Hannerz, F.; Lotsch, A. *Assessment of Land Use and Cropland Inventories for Africa*; CEEPA Discussion Papers 22; Centre of Environmental Economics and Policy in Africa, University of Pretoria: Pretoria, South Africa, 2006.
195. Griffin, S.; Kunz, E. Data fusion and integration of high and medium resolution imagery for crop analysis. In Proceedings of the ASPRS 2009 Annual Conference, Baltimore, MD, USA, 9–13 March 2009.
196. Fahimnejad, H.; Soofbaf, S.R.; Alimohammadi, A.; Zoj, M.V. Crop type classification by Hyperion Data and Unmixing Algorithm. 2007. Available online: https://www.geospatialworld.net/wp-content/uploads/images/pdf/MWF_Poster_40.pdf (accessed on 12 May 2021).
197. Gao, F.; Masek, J.; Schwaller, M.; Hall, F. On the blending of the Landsat and MODIS surface reflectance: Predicting daily Landsat surface reflectance. *IEEE Trans. Geosci. Remote Sens.* **2006**, *44*, 2207–2218. [[CrossRef](#)]
198. Fu, D.; Chen, B.; Wang, J.; Zhu, X.; Hilker, T. An Improved Image Fusion Approach Based on Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model. *Remote Sens.* **2013**, *5*, 6346–6360. [[CrossRef](#)]
199. Zurita-Milla, R.; Kaiser, G.; Clevers, J.G.P.W.; Schneider, W.; Schaepman, M.E. Downscaling time series of MERIS full resolution data to monitor vegetation seasonal dynamics. *Remote Sens. Environ.* **2009**, *113*, 1874–1885. [[CrossRef](#)]
200. Amorós-López, J.; Gómez-Chova, L.; Alonso, L.; Guanter, L.; Zurita-Milla, R.; Moreno, J.; Camps-Valls, G. Multitemporal fusion of Landsat/TM and ENVISAT/MERIS for crop monitoring. *Int. J. Appl. Earth Obs. Geoinf.* **2013**, *23*, 132–141. [[CrossRef](#)]
201. Luo, Y.; Guan, K.; Peng, J. STAIR: A generic and fully-automated method to fuse multiple sources of optical satellite data to generate a high-resolution, daily and cloud-/gap-free surface reflectance product. *Remote Sens. Environ.* **2018**, *214*, 87–99. [[CrossRef](#)]
202. Houborg, R.; McCabe, M.F. A Cubesat enabled Spatio-Temporal Enhancement Method (CESTEM) utilizing Planet, Landsat and MODIS data. *Remote Sens. Environ.* **2018**, *209*, 211–226. [[CrossRef](#)]
203. Wang, Q.; Atkinson, P.M. Spatio-temporal fusion for daily Sentinel-2 images. *Remote Sens. Environ.* **2018**, *204*, 31–42. [[CrossRef](#)]

204. Yuan, L.; Zhang, J.C.; Shi, Y.Y.; Nie, C.W.; Wei, L.G.; Wang, J.H. Damage Mapping of Powdery Mildew in Winter Wheat with High-Resolution Satellite Image. *Remote Sens.* **2014**, *6*, 3611–3623. [[CrossRef](#)]
205. Zhang, D.Y.; Zhou, X.G.; Zhang, J.; Lan, Y.B.; Xu, C.; Liang, D. Detection of rice sheath blight using an unmanned aerial system with high-resolution color and multispectral imaging. *PLoS ONE* **2018**, *13*. [[CrossRef](#)]
206. Gao, D.M.; Sun, Q.; Hu, B.; Zhang, S. A Framework for Agricultural Pest and Disease Monitoring Based on Internet-of-Things and Unmanned Aerial Vehicles. *Sensors* **2020**, *20*, 1487. [[CrossRef](#)]
207. Zheng, Q.; Huang, W.J.; Cui, X.M.; Shi, Y.; Liu, L.Y. New Spectral Index for Detecting Wheat Yellow Rust Using Sentinel-2 Multispectral Imagery. *Sensors* **2018**, *18*, 868. [[CrossRef](#)]
208. Isip, M.F.; Alberto, R.T.; Biagtan, A.R. Exploring vegetation indices adequate in detecting twister disease of onion using Sentinel-2 imagery. *Spat. Inf. Res.* **2020**, *28*, 369–375. [[CrossRef](#)]
209. Prabhakara, K.; Hively, W.D.; Mccarty, G.W. Evaluating the relationship between biomass, percent groundcover and remote sensing indices across six winter cover crop fields in Maryland, United States. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *39*, 88–102. [[CrossRef](#)]
210. Shammi, S.A.; Meng, Q. Use time series NDVI and EVI to develop dynamic crop growth metrics for yield modeling. *Ecol. Indic.* **2021**, *121*, 107124. [[CrossRef](#)]
211. Gitelson, A.A.; Viña, A.; Verma, S.B.; Rundquist, D.C.; Arkebauer, T.J.; Keydan, G.; Leavitt, B.; Ciganda, V.; Burba, G.G.; Suyker, A.E. Relationship between gross primary production and chlorophyll content in crops: Implications for the synoptic monitoring of vegetation productivity. *J. Geophys. Res. Atmos.* **2006**, *111*. [[CrossRef](#)]
212. Houborg, R.; Cescatti, A.; Migliavacca, M.; Kustas, W.P. Satellite retrievals of leaf chlorophyll and photosynthetic capacity for improved modeling of GPP. *Agric. For. Meteorol.* **2013**, *177*, 10–23. [[CrossRef](#)]
213. Dash, J.; Curran, P. Evaluation of the MERIS terrestrial chlorophyll index (MTCI). *Adv. Space Res.* **2007**, *39*, 100–104. [[CrossRef](#)]
214. Zhang, S.; Liu, L. The potential of the MERIS Terrestrial Chlorophyll Index for crop yield prediction. *Remote Sens. Lett.* **2014**, *5*, 733–742. [[CrossRef](#)]
215. Maxwell, K.; Johnson, G.N. Chlorophyll fluorescence—A practical guide. *J. Exp. Bot.* **2000**, *51*, 659–668. [[CrossRef](#)]
216. Guanter, L.; Alonso, L.; Gómez-Chova, L.; Amoros-Lopez, J.; Vila, J.; Moreno, J. Estimation of solar-induced vegetation fluorescence from space measurements. *Geophys. Res. Lett.* **2007**, *34*. [[CrossRef](#)]
217. Joiner, J.; Yoshida, Y.; Vasilkov, A.P.; Corp, L.A.; Middleton, E.M. First observations of global and seasonal terrestrial chlorophyll fluorescence from space. *Biogeosciences* **2011**, *8*, 637–651. [[CrossRef](#)]
218. Frankenberg, C.; Fisher, J.; Worden, J.; Badgley, G.; Saatchi, S.S.; Lee, J.-E.; Toon, G.C.; Butz, A.; Jung, M.; Kuze, A.; et al. New global observations of the terrestrial carbon cycle from GOSAT: Patterns of plant fluorescence with gross primary productivity. *Geophys. Res. Lett.* **2011**, *38*. [[CrossRef](#)]
219. Parazoo, N.C.; Bowman, K.; Fisher, J.; Frankenberg, C.; Jones, D.B.A.; Cescatti, A.; Perez-Priego, O.; Wohlfahrt, G.; Montagnani, L. Terrestrial gross primary production inferred from satellite fluorescence and vegetation models. *Glob. Chang. Biol.* **2014**, *20*, 3103–3121. [[CrossRef](#)] [[PubMed](#)]
220. Guan, K.; Berry, J.A.; Zhang, Y.; Joiner, J.; Guanter, L.; Badgley, G.; Lobell, D. Improving the monitoring of crop productivity using spaceborne solar-induced fluorescence. *Glob. Chang. Biol.* **2016**, *22*, 716–726. [[CrossRef](#)]
221. Harris, R. Earth observation and UK science policy. *Space Policy* **2002**, *18*, 205–213. [[CrossRef](#)]
222. Tonneau, J.-P.; Bégué, A.; Leroux, L.; Augusseau, X.; Faure, J.-F.; Mertens, B.; Pinet, C.; Tomasini, L. Geospatial information for African agriculture: A key investment for agricultural policies. *Perspective* **2019**, *51*, 1–4. [[CrossRef](#)]
223. Begue, A.; Leroux, L.; Soumare, M.; Faure, J.F.; Diouf, A.A.; Augusseau, X.; Tonneau, J.P. Remote Sensing Products and Services in Support of Agricultural Public Policies in Africa: Overview and Challenges. *Front. Sustain. Food Syst.* **2020**, *4*. [[CrossRef](#)]
224. Ustin, S.L.; Middleton, E.M. Current and near-term advances in Earth observation for ecological applications. *Ecol. Process.* **2021**, *10*, 1–57. [[CrossRef](#)] [[PubMed](#)]
225. UNECA. *Geospatial Information for Sustainable Development in Africa—African Action Plan on Global Geospatial Information Management 2016–2030*; United Nations Economic Commission for Africa (UNECA): Addis Ababa, Ethiopia, 2017.
226. Saah, D.; Tenneson, K.; Matin, M.; Uddin, K.; Cutter, P.; Poortinga, A.; Nguyen, Q.H.; Patterson, M.; Johnson, G.; Markert, K.; et al. Land Cover Mapping in Data Scarce Environments: Challenges and Opportunities. *Front. Environ. Sci.* **2019**, *7*, 150. [[CrossRef](#)]