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A systematic review on the use of remote sensing technologies in quantifying grasslands ecosystem services

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ABSTRACT

The last decade has seen considerable progress in scientific research on vegetation ecosystem services. While much research has focused on forests and wetlands, grasslands also provide a variety of different provisioning, supporting, cultural, and regulating services. With recent advances in remote sensing technology, there is a possibility that Earth observation data could contribute extensively to research on grassland ecosystem services. This study conducted a systematic review on progress, emerging gaps, and opportunities on the application of remote sensing technologies in quantifying all grassland ecosystem services including those that are related to water. The contribution of biomass, Leaf Area Index (LAI), and Canopy Storage Capacity (CSC) as water-related ecosystem services derived from grasslands was explored. Two hundred and twenty-two peer-reviewed articles from Web of Science, Scopus, and Institute of Electrical and Electronics Engineers were analyzed. About 39% of the studies were conducted in Asia with most of the contributions coming from China while a few studies were from the global south regions such as Southern Africa. Overall, forage provision, climate regulation, and primary production were the most researched grassland ecosystem services in the context of Earth observation data applications. About 39 Earth observation sensors were used in the literature to map grassland ecosystem services and MODIS had the highest utilization frequency. The most widely used vegetation indices for mapping general grassland ecosystem services in literature included the red and near-infrared sections of the electromagnetic spectrum. Remote sensing algorithms used within the retrieved literature include process-based models, machine learning algorithms, and multivariate techniques. For water-related grassland ecosystem services, biomass, CSC, and LAI were the most prominent proxies characterized by remotely sensed data for understanding evapotranspiration, infiltration, run-off, soil water availability, groundwater restoration and surface water balance. An understanding of such hydrological processes is crucial in providing insights on water redistribution and balance within grassland ecosystems which is important for water management.

1. Introduction

Grasslands represent the most extensive land cover on the earth's surface (Briske 2017). They are a mixture of grass, clover, and other leguminous species, herbs, and shrubs and are generally managed as natural ecosystems (Carlier et al. 2009; Zerga 2015). Grasslands are particularly important because they occupy a large area of rangeland vegetation types, covering 31.5% of the global landmass and occurring naturally on all continents excluding Antarctica (Latham et al. 2014). Globally, grasslands are recognized for their significant role in biodiversity conservation and the provision of a variety of ecosystem services (Habel et al. 2013; Jin et al. 2014).

The last decade has seen rapid progress in ecosystem services (ES) related research activities. While the past research mostly focused on forests and wetlands, grasslands were largely neglected, yet they also provide a variety of provisioning (forage production, genetic resources), supporting (nutrient cycling, primary production), cultural (recreation, educational), and regulating (water regulation, climate regulation)

ecosystem services (Havstad et al. 2007; Zhao et al. 2020). Grassland ES refer to physical and non-physical resources provided by ecosystem structure and functioning of grasslands to meet human survival as well as biodiversity maintenance (Lemaire, Hodgson, and Chabbi 2011; Sala et al. 2017). This implies that accurate and timely information about the geographic extent and health condition of grasslands is of crucial importance for the management of this natural capital.

One of the most valuable services provided by grasslands is that of water management. In terms of water flow regulation, grasslands mainly occur in the main catchment areas (Cadman, De Villiers, and Lechmere-Oertel 2013). As such, they form an effective system for water capture by inducing high infiltration rates, reducing run-off and soil erosion while regulating streamflows (Egoh et al. 2011; Cadman, De Villiers, and Lechmere-Oertel 2013). However, grasslands are becoming more vulnerable to land-use changes (Alkemade et al. 2013), alien plant invasion (Seastedt and Pyšek 2011) and climate change (Bellocchi and Picon-Cochard 2021). Such threats compromise their ecosystem productivity resulting in the deterioration of the role of grassland biomes in water flow regulation.

Grass biophysical parameters such as biomass, leaf area index (LAI) and canopy storage capacity (CSC) are prominent attributes that could offer valuable information to understand hydrological processes and water balance within grasslands (Xu et al. 2006; Bulcock and Jewitt 2010). Biomass refers to the mass of plant organic matter per unit area (Pang et al. 2020). It is a critical component of global carbon cycling and it directly influences hydrological processes such as surface run-off and infiltration (Duley and Domingo 1949; Jin et al. 2014). LAI is the ratio of a leaf area per unit ground surface area (Zheng and Monika Moskal 2009). It is a major control of vegetation productivity, biophysical feedback on atmospheric energy and water exchanges (Law, Cescatti, and Baldocchi 2001). CSC is the amount of water retained in plant canopies that controls rainfall interception, evaporation from vegetation canopy, throughfall, interception, infiltration, and ground water restoration (Bulcock and Jewitt 2010; Zou et al. 2015).

Remote sensing has become a cost-effective tool for regional and global mapping (Feng et al. 2010), modeling (Andrew, Wulder, and Nelson 2014) and quantifying ecosystem properties (Barbosa et al. 2015). Several studies (Ustin et al. 2004; Jiang et al. 2007; Muraoka and Koizumi 2009; Vargas, Willemen, and Hein 2019; del Río-Mena et al. 2020; Niu et al. 2021; Wang et al. 2021) have demonstrated the capability of remote sensing technologies in quantifying ES. A notable advantage of Earth observation technologies is their capability to provide synoptic, unlimited, spatially explicit, and frequent information at varying spatial and temporal resolutions (Xu et al. 2008; Wachendorf, Fricke, and Möckel 2018). With recent advances in remote sensing technology, there is a possibility that Earth observation data could contribute extensively to research on grasslands ES (Soubry et al. 2021).

In terms of literature, grasslands ecosystem reviews have been carried out (Ceotto 2008; Prochnow et al. 2009a, 2009b; Pablo et al. 2016; Zhao et al. 2020). However, most of the above-mentioned reviews did not focus on remote sensing applications in grassland ES. Within the remote sensing context, there are a number of reviews that look at the development and significant advances of remote sensing technologies within grassland studies (Ali et al. 2016; Wachendorf, Fricke, and Möckel 2018; Reinermann, Asam, and Kuenzer 2020). To the best of our knowledge, the aforementioned studies did not conduct any bibliometric analysis of the studies that focus on remote sensing of ES provided by grasslands, with particular attention to their accuracies. Additionally, few studies have assessed literature on the utility of remote sensing on deriving grasslands biophysical parameters with a special interest in characterizing water-related grassland ES (Soubry et al. 2021). The recent systematic review by Soubry et al. (2021) specifically looked at the application of geospatial techniques in characterizing ecosystem health attributes, indicators, and measures of forest and grassland. Nevertheless, the study focused on ecological indicators and attributes derived from GIS and remote-sensing data in the context of ecosystem health assessment, not the application of Earth observation data in characterizing ES provided by grassland ecosystems, with particular attention to model accuracies.

Therefore, the current study conducted a systematic literature review to understand the progress, emerging gaps and opportunities on the use of remote sensing technologies in quantifying grasslands ES including those that are related to water. The study seeks to further explore the contribution of variables such as biomass, LAI, and CSC in water management. An understanding of the contribution of such parameters will provide insights of their significant role in the hydrological cycle. This will, in turn, assist water resource managers to facilitate mapping hotspot areas for interventions within degraded grasslands.

2. Materials and methods

2.1 Literature search, inclusion, and exclusion strategy

The studies included in this systematic literature review were retrieved through an extensive search for peer-reviewed journal articles published in Web of Science (WOS), Scopus and Institute of Electrical and Electronics Engineers (IEEE). The following search terms combination were used in all the three databases: "grassland productivity AND remote sensing OR GIS," "grassland productivity monitoring," "grassland ecosystems AND remote sensing OR GIS," "grassland ecosystem services AND remote sensing OR GIS," "grassland LAI AND remote sensing OR GIS," "grassland canopy storage capacity AND remote sensing," "grassland productivity AND water management AND remote sensing OR GIS." The literature search was conducted without any restrictions on the year of publication.

A total of 784 references from WOS, 773 from Scopus and 89 references from IEEE were collected. Following the literature search, the retrieved references (n = 1646) were exported in Endnote for screening. The number of studies identified, included, or excluded were recorded following the Preferred Reporting Items for Systematic Reviews and Meta-analysis statement (Page et al. 2021) (Figure 1). The articles eligible for the meta-analysis had to meet the following criteria:

(1) The study focuses on grasslands and no other vegetation types (e.g. forests, crops) are included since those will be denoting different ecosystems.

(2) The study focuses on grasslands productivity concepts (biophysical and biochemical parameters of grasslands).
(3) The study is based on GIS or remote-sensing techniques in grassland productivity monitoring and management.
(4) Results or prediction accuracies of remote sensing technology (sensors or algorithms or vegetation indices) used in the study are stated.
(5) The article is published in an accredited journal.
(6) The article is written in English.

From the retrieved literature searches, the study carried out the first exclusion process of removing all duplicates. In total, 641 records were excluded. Secondly, essential bibliography information (title and abstract) of the remaining articles (n = 1005) were examined to check whether the studies applied remote sensing to examine grasslands parameters. Upon title and abstract screening, irrelevant articles (n = 819) were excluded including studies that were not written in English. Of the 186 articles remaining, 45 of them were unavailable in portable document format (pdf), and inaccessible in full length. As a result, they were excluded. The remaining 141 articles were assessed for eligibility and additional articles (n = 81) were identified through the reference lists of the included articles using the backward reference searching (Horsley, Dingwall, and Sampson 2011). These were retrieved using the Google scholar web search engine. In total, 222 articles met the selection criteria and were used for data extraction.

2.2 Data extraction

The data from Endnote was exported into an excel spreadsheet. Endnote was set to export key bibliographic information such as author name, publication year, article title, journal name, keywords, abstract digital object identifier (DOI), uniform resource locator (URL). In addition to this, information on study area location (country and continent), Earth observation sensor technology utilized, type of vegetation indices, remote sensing algorithms with special attention on derived accuracies and biophysical or biochemical parameter(s) being investigated were extracted after reading through each article. With regard to accuracies, the root mean square error values were not used in this
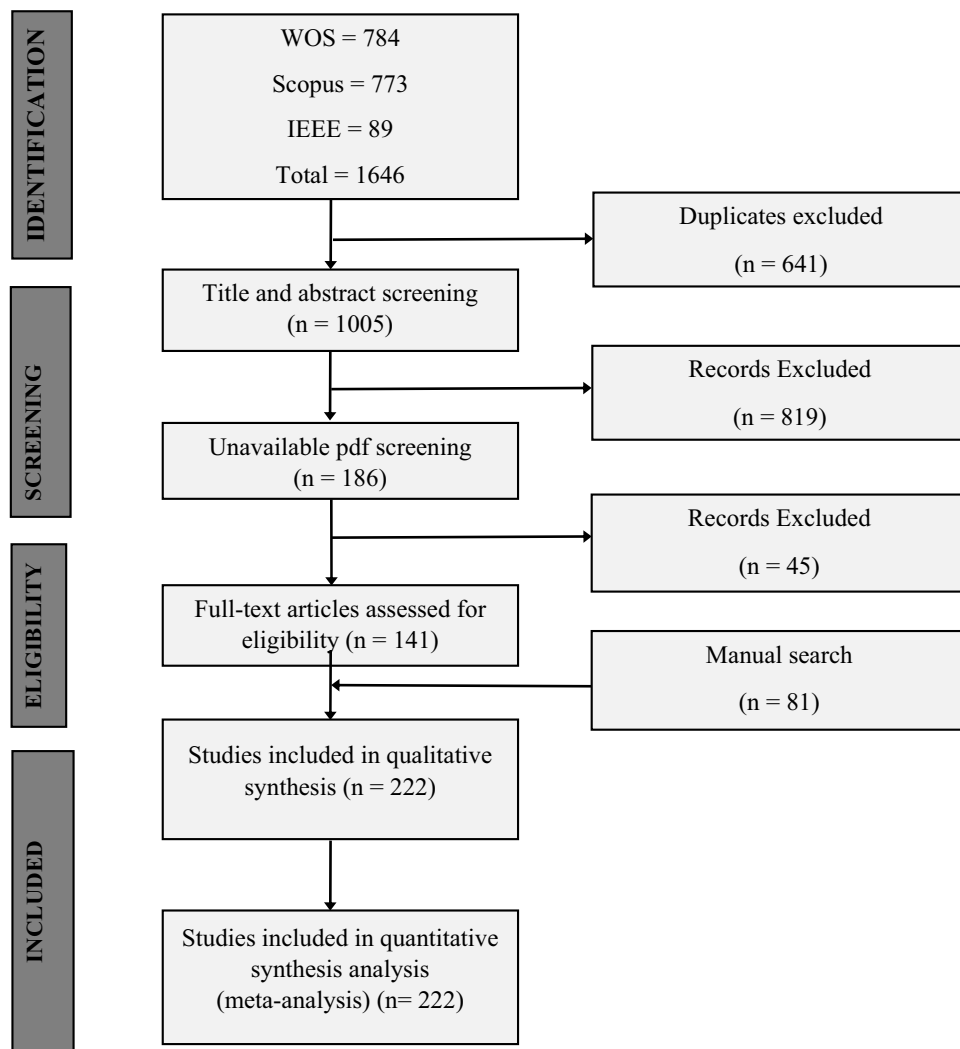
Figure 1. PRISMA flow diagram for selection of studies considered in the review.

study because ES variables are measured in different SI units. Consequently, the coefficient of determination (R^2) value was used in assessing the accuracies derived in estimating these grasslands ES. The R^2 value is a common accuracy estimation parameter used to explain the magnitude of variation between the predicted and measured samples of a specific grassland variable also known as the goodness of the model's fit (Cameron and Windmeijer 1997; Chicco, Warrens, and Jurman 2021). The R^2 ranges from 0 to 1, with values closer to 1 indicating a great model fit or a more accurate model depending on what is predicted (Singh et al. 2017). The frequency of articles was used in this study for quantification purposes. Specifically, the measures used for the extracted data included counts and percentages while the R^2s were extracted from respective manuscripts.

2.3 Data analysis

The retrieved articles and extracted data were subjected to quantitative and qualitative synthesis and analysis. Firstly, bibliometric analysis was performed to visualize occurrence and co-occurrence networks of key terms from the retrieved literature. Bibliometric analysis is a widely used meta-analytical tool that can identify interconnections of key terms related to a given topic or field from published papers (Han et al. 2020). This was carried out using VOSviewer software (Eck, Jan, and Waltman 2010). VOSviewer provides network visualization of key terms in the form of linked clusters. Creating a map in VOSviewer include four steps which are:

(1) Selecting a counting method (binary counting or full counting).

(2) Selecting minimum number of occurrences for a term (calculating similarity index).
(3) Calculating relevance score for the co-occurrence terms and based on this score, display most relevant items
(4) Displaying a map based on the selected terms.

The functionality of VOSviewer for bibliometric mapping and analysis is detailed in Eck, Jan, and Waltman (2010). The titles, abstracts, and keywords of the final database were used as input text data in VOSviewer to provide graphical visualization based on occurrence and co-occurrence of key terms.

To assess the progress of remote sensing technologies in grassland ES, basic statistical frequencies and trend analysis were conducted using Microsoft Excel (Carlberg 2014). ES provided by grasslands were categorized using the classification scheme proposed by the Millennium ecosystem assessment report (MA, Millennium Ecosystem Assessment 2005) (Table 1). The Millennium Assessment (MA) classification scheme was chosen following its present wide recognition as a robust classification approach in distinguishing ecosystem functions into regulating, provisioning, supporting and cultural services.

Grassland biophysical and biochemical parameters are key indicators of ecosystem services (Lavorel et al. 2011). Given this context, biophysical and biochemical parameters were used to identify ES within the reviewed studies. Additionally, biochemical parameters relating to chemical components such as chlorophyll content and nitrogen concentration are an indirect measure of vegetation nutrient status which in turn relates to nutrient regulation services (Tong and Yuhong 2017; Wang et al. 2017). Therefore, studies relating to the proportion of nitrogen and chlorophyll concentration were classified under nutrient regulation service.

The review was then separated into two sections to address the research objectives. The first section explored the progress in remote sensing technologies applied in grassland ES. This section detailed the literature search characteristics, identified ecosystem services, trends in the distribution of studies and remote sensing technologies applied within grassland ES studies. The outcomes of the first phase were then used to articulate existing research gaps on the role of remote sensing in quantifying grassland water-related ES in the second phase.

3. Results

3.1 Literature search characteristics

In analyzing literature characteristics of the retrieved studies, the network map in Figure 2 categorized the identified literature into four clusters of concepts. The

Table 1. Non-exhaustive grassland-related ecosystem services classification based on Millennium ecosystem assessment as explained in Leemans and De Groot (2003).

| Category	Ecosystem service	Explanation
Provisioning services	Food (fodder)	Range of food products derived from plants, animals, and microbes.
	Genetic resources	Genes and genetic information used for animal and plant breeding and biotechnology.
	Fresh water	Water is obtained from different water ecosystems (dams, rivers, oceans).
Regulating services	Climate regulation	Regulation processes related to the greenhouse effect, atmospheric chemical composition, ozone layer, and atmospheric weather conditions at both local and global scales. Regulation of both temperature and precipitation at a local scale. On a global scale, ecosystems play an important role in climate by Carbon sequestration storage.
	Water regulation	Regulation of hydrological flows, water storage and water retention (i.e. timing and magnitude of runoff, flooding, aquifer recharge and the system's water storage potential) are regulated by changes in land cover.
	Air quality regulation	Sequestration and storage of carbon as well as the release of oxygen, influence air quality.
	Erosion regulation	Soil retention and regulation of soil erosion and landslides.
	Water purification and waste treatment	Purification of water through filtering out and decomposing organic wastes introduced into inland waters, coastal and marine ecosystems.
	Natural hazard regulation	Ecosystems can dramatically regulate the damage caused by landslides, wildfires etc.
Supporting services	Nutrient cycling	Nutrients such as nitrogen, and phosphorus cycle through ecosystems.
	Primary production or photosynthesis	Assimilation of energy and nutrients by biota. Production of energy required by most living organisms through photosynthesis.
	Habitat	Providing living spaces for animals or plants while maintaining biodiversity.
	Soil formation	Soil formation and changes in soil formation which impact human well-being
Cultural services	Recreation and ecotourism	Provision of recreational parks and touristic attractions.
	Educational values	Provide a basis for both formal and informal education in societies.
	Esthetic values	Provide esthetic value in the light of urban development.
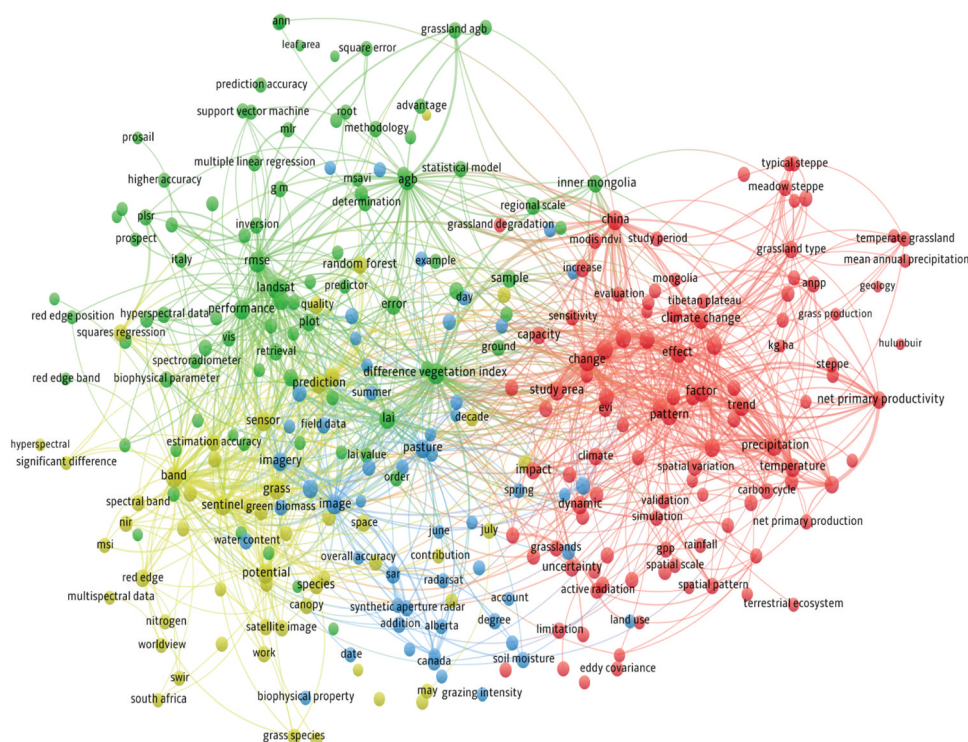
Figure 2. Topical concepts in grasslands ecosystem services studies derived using data from titles, abstract and keywords.

green cluster had its key terms being "prediction accuracy," "performance," "ann," "support vector machines," "multiple linear regression," "plsr," "prospect," "random forest" "biophysical parameters." This cluster links accuracy assessment of algorithm performance with estimating biophysical parameters. The inclusion of terms such as "Landsat," "hyperspectral data," "spectroradiometer" in this cluster presents the linkage between satellite imagery, ground-level spectral reflectance, remote sensing modeling techniques, and principal biophysical parameters, which directly implies the utility of various remote sensing technologies in grasslands ecosystem services.

The second cluster (yellow) had its key terms as "band," "spectral bands," "sensor," "red-edge," "sentinel," "worldview." This relates to the influence of the spectral band settings (reflectance measured) on the sensor's performance in estimating grass productivity (Wang et al. 2019b). The blue cluster had "synthetic aperture radar" and "soil moisture" as its key terms which directly implies the potential of synthetic aperture radar (SAR) sensors in estimating soil moisture content. Lastly, the red cluster connected terms such as "China," "modis ndvi," "carbon cycle." This articulates the wide usage of MODIS derived NDVI as a proxy for studying grasslands as a major component of carbon

cycling, with most studies carried out in China (Xinyu et al. 2014; Liu et al. 2017; Kong et al. 2019). The red cluster also categorized terms such as "climate change," "net primary productivity," "precipitation," "temperature." Precipitation and temperature are crucial variables in controlling net primary production which is a key measure of ecosystem functioning used in understanding global climate change (Jia et al. 2015).

3.2 Progress in the use of remote sensing technologies to monitor grasslands ecosystem services

3.2.1 Grassland ecosystem services identified in literature

Results of this study illustrate that nine-grassland ES were mentioned in the retrieved articles (Figure 3). A total of 79 studies utilized remote sensing in studying grassland provisioning services of which forage provision had the highest frequency of studies (n = 75). Forty-three studies investigated grassland supporting services relating to primary production, 17 studies focused on nutrient cycling and thirteen studies were based on habitat for wildlife species. Seventy-five studies focused on grassland regulating services, of which 51 studies focused on climate regulation. The results show that
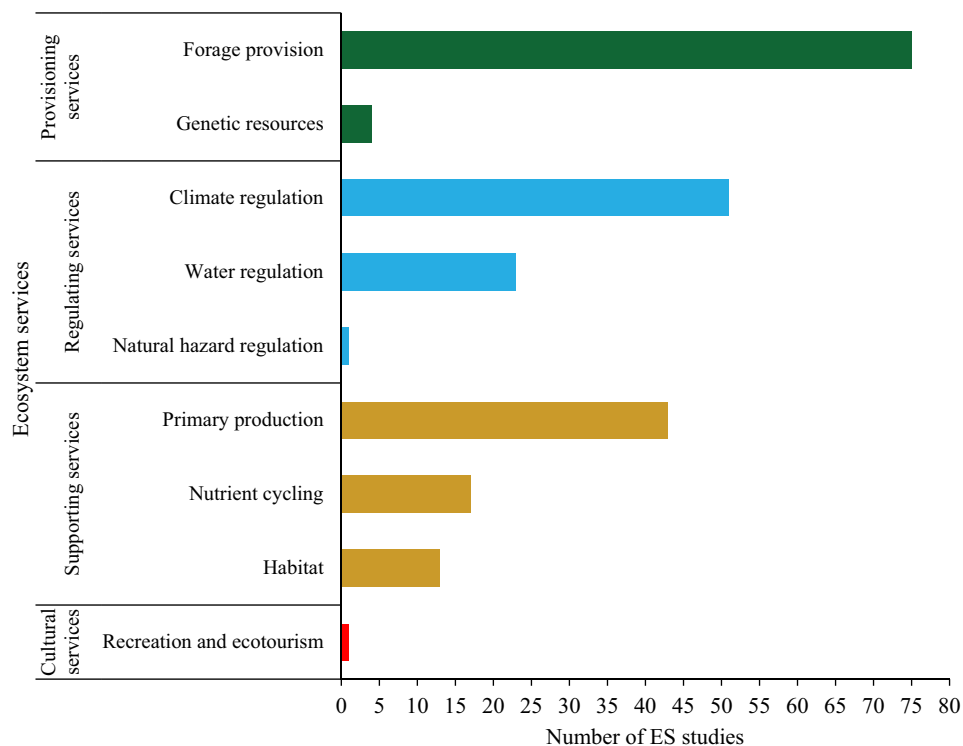
Figure 3. The number of studies that utilized remote sensing to assess grasslands ecosystem services. Studies with multi-ecosystem services were counted several times.

only one study (Quansheng et al. 2014) utilized Earth observation data to monitor grasslands tourist seasons that relates to cultural ecosystem services.

For water regulation service, three studies (Davidson, Wang, and Wilmshurst 2006; Hajj et al. 2014; Sibanda et al. 2021) evaluated the utility of remotely sensed data in mapping moisture content elements related to biomass. In addition, studies by Pan and Shangguan (2006) and Kautz et al. (2019) used the spatial extent of vegetation cover derived using remotely sensed data to estimate run-off while Xing et al. (2014) use it to estimate soil moisture within grasslands. Meanwhile, five studies (Shimoda and Oikawa 2008; Vetter, Schaffrath, and Bernhofer 2012; Schaffrath and Bernhofer 2013; Zhu et al. 2013; Castelli et al. 2018) utilized remotely sensed data to characterize LAI in the context of hydrological models linked to evapotranspiration. Remotely sensed LAI was also used as input data to understand hydrological processes relating to water balance (Nouvellon et al. 2001; Sridhar and Wedin 2009), ecological water requirement (Zhang et al. 2010) and precipitation use efficiency (Jia et al. 2015) within grassland

ecosystems. Aiming, Murray, and Richter (2017) used process-based models which simulate LAI as a dynamic input in a grass growth model. The model was used to estimate evapotranspiration, drainage, and water productivity within different grassland systems.

In terms of CSC, one study (Yu et al. 2012) utilized water budget balance and artificial wetting methods to model canopy rainfall storage capacity in relation to grassland degradation and its impact on the hydrological cycle. Additionally, a study by Sibanda et al. (2021) utilized remote sensing methods to assess grassland CSC. Three studies (Bertoldi et al. 2014; Baghdadi et al. 2015; El; Hajj et al. 2015) were based on the use of remotely sensed data to estimate soil moisture content in grasslands which is a key parameter for many hydrological processes. Paruelo et al. (1999) used remotely sensed aboveground net primary production data as an estimate of water availability within grasslands. Saatchi, van Zyl, and Asrar (1995) used synthetic aperture radar (SAR) data to estimate soil moisture and canopy water content of natural grasslands which is of fundamental importance to understanding eco-hydrological processes.
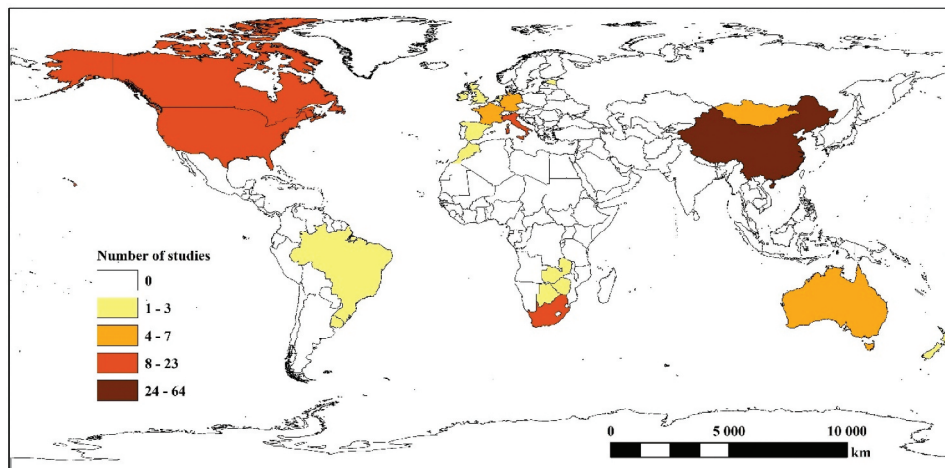
Figure 4. Spatial distribution of remote sensing studies in the context of grassland ecosystem services. Studies conducted at regional and global scales are not shown.

3.2.2 Geographic distribution and publication trends

In terms of spatial distribution, the studies included in the meta-analysis were conducted in 31 different countries (Figure 4). Ten articles were large-scale studies conducted at a regional scale and two studies (Xia et al. 2014; Yang et al. 2017) were conducted on a global scale. These studies were included in the meta-analysis but could not be classified under a certain country in Figure 4. In assessing the frequency of publications per nation, it was observed that studies on grasslands ES were conducted across all continents excluding Antarctica. Thirty-three per cent of these studies were conducted in Asia, with China having most studies.

Although 18% of the studies were conducted in Africa, (13%) were conducted in Southern Africa, mostly in South Africa. About 22% of the studies were conducted in Europe, 18% in North America, 5% in South America, and 3% in Australia. 1% of the studies collected in this study were conducted at a global-scale. From Figure 4, considerable gaps in the geographic distribution of published articles can be observed especially in South America, Australia, and most parts of Africa. Interestingly, 11 out of 23 studies on water-related ecosystem services were conducted in the global south and 12 in the global north. More research efforts need to be exerted toward the utilization of remotely sensed data in assessing grassland water-related ES globally.
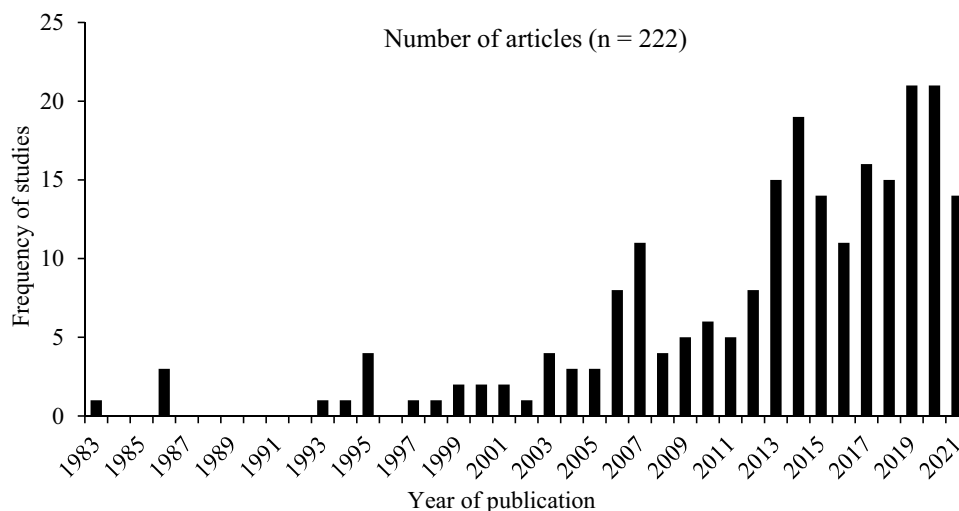

Figure 5. Frequency of studies published on remote sensing applications in grassland ecosystem services.
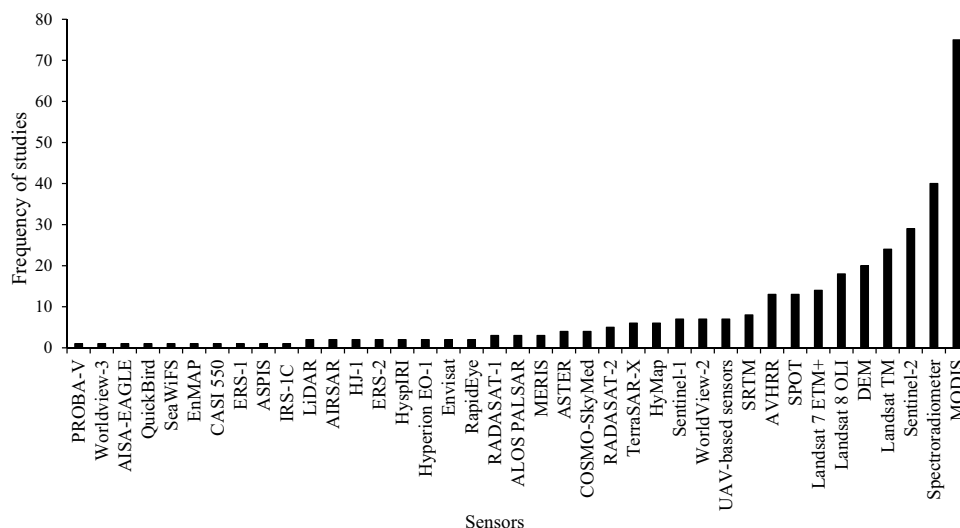
Figure 6. Frequency of studies that utilized a specific sensor system within reviewed studies. Studies with multi-sensors were counted several times.

The earliest publication of grassland ES was in 1983 (Figure 5). Meanwhile, few articles (n = 10) were published between 1983 and 1996. A constant number of publications occurred between 1997 and 2001 after which a considerable fluctuation in publications was observed. Since then, the use of remote sensing in grassland ES studies has been increasing steadily reaching a total of 222 published articles in 2021 (Figure 5).

3.2.3 Sensor technologies, spectral settings, and derived vegetation indices

The use of Earth observation sensors used in remote sensing of grassland ES studies has considerably increased. Thirty-nine sensor types were noted in the literature reviewed (Figure 6). As illustrated in the characterization of literature in Figure 2 (red cluster), Moderate Resolution Imaging Spectroradiometer (MODIS) had the highest frequency of studies (34%), followed by the Landsat system (25% (TM = 11%, OLI = 8%, ETM+ = 6%)).

Meanwhile, a significant number of studies (18%) have used handheld hyperspectral devices for the in-situ acquisition of remotely sensed data for characterizing grass biophysical and biochemical parameters. The findings of this study also illustrate that 14% of the studies utilized digital elevation models (DEM) in estimating and mapping grassland ecosystem services. Of these studies, about 4% specifically used the Shuttle Radar Topography Mission (STRM) and

2% used the Advanced Spaceborne Thermal Emmision and Reflection Radiometer (ASTER) derived digital elevation models.

The new generation of sensors such as Sentinel 2 multispectral instrument (MSI) has shown great potential in grassland ES studies (13%). High spatial resolution satellites such as Worldview-2 and Worldview-3 have also been utilized in 3% of the studies. Although applied in a few studies, results from the searched literature showed that recent technologies in remote sensing such as the Unmanned Aerial Vehicle (UAV)-based sensors have also been utilized in grasslands ES studies (3%) (Figure 6).

Results show that the use of sensors such as Advanced Very High-Resolution Radiometer (AVHRR), spectroradiometer and platforms such as UAVs started trending within the 1980's (Figure 7). The 1990's saw the introduction of sensors such as SPOT and Landsat TM sensor-system within the grassland ES research. The use of MODIS sensor can be observed from 2005 and it has been used almost in all years. Additionally, the use of Landsat ETM+ started trending in 2001 up until now. Although the results show that Worldview-2 had also been utilized in mapping grassland ES, it was observed to have been utilized for five years, from 2013 to 2018. The period from 2014 to 2021 witnessed a shift in the frequent use of Sentinel-2 and Landsat 8 OLI sensors.
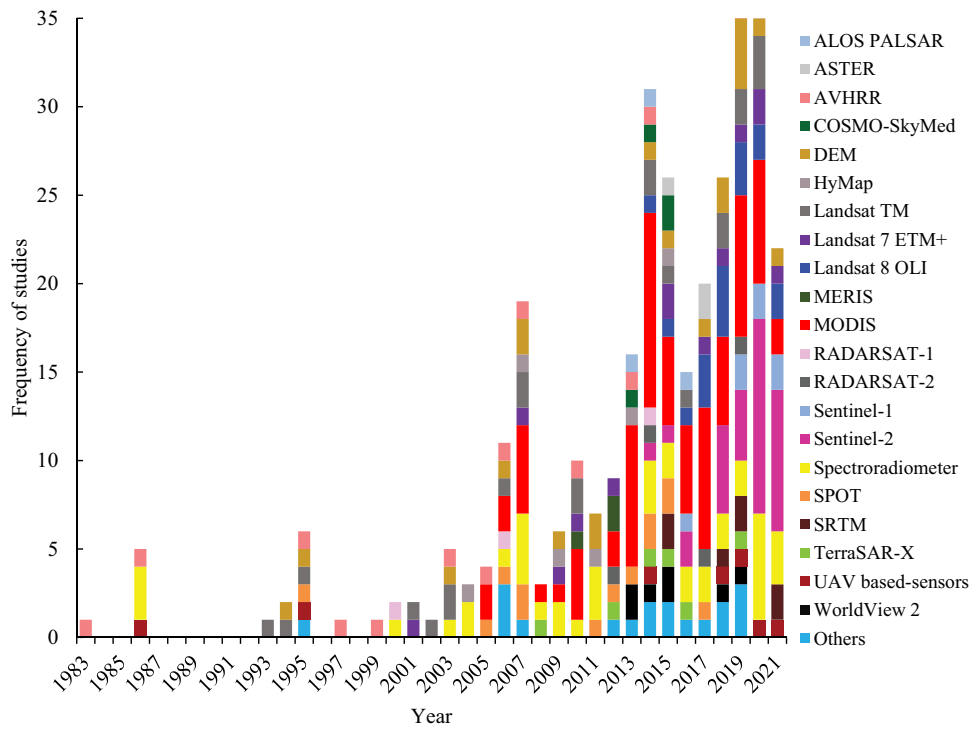
Figure 7. Progression of Earth observation sensors used within the reviewed studies between December 1983 and September 2021.

The sensors used in the grassland ES studies show a high range of average prediction accuracies with R^2 values of 55% to 90.5% (Figure 8). The highest average R^2 value (90.5%) was obtained from the utility of UAVs. Meanwhile, freely available moderate spatial resolution satellites such as Landsat TM, OLI, and ETM+ had high mean prediction accuracies of 70, 76, and 83%, respectively. Additionally, the high spatial resolution Sentinel 2 satellite data yielded a high mean prediction accuracy of 77%. Interestingly, SAR systems yielded considerable average prediction accuracies ranging from 58% to 73% (Figure 8).

Numerous vegetation indices have been derived from Earth observation sensors for mapping and monitoring grasslands ES. Although a plethora of vegetation indices were identified in the literature

Figure 8. Box plots showing average correlation coefficients values for Earth observation sensors used in the ecosystem services studies. Sensors utilized in less than three studies are excluded.

Table 2. Summary of the commonly used vegetation indices in grassland ecosystem services studies.

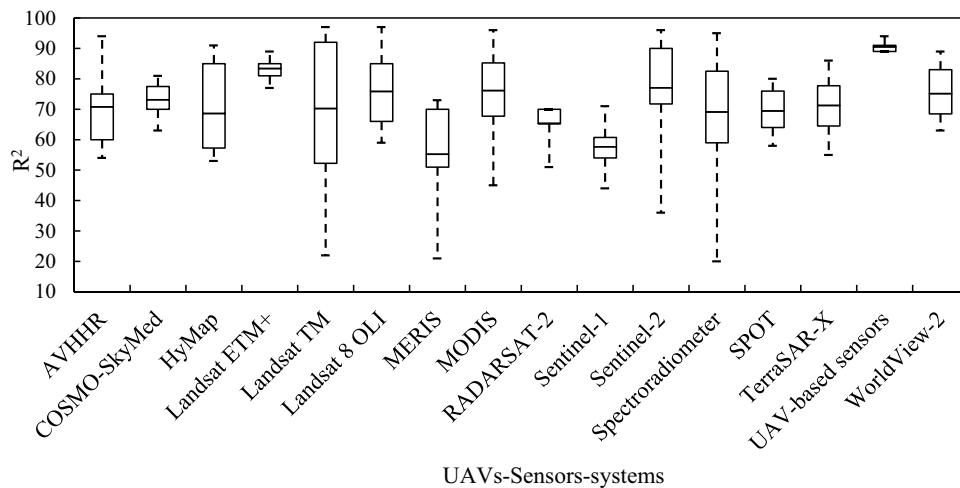| Index name	Abbreviation	Formula	R^2 range	Reference
Enhanced Vegetation Index	EVI	$G \frac{NIR-RED}{NIR+C1 \times RED - C2 \times BLUE + L}$	0.44–0.95	(Liu and Huete 1995)
Normalized difference vegetation index	NDVI	$\frac{NIR-RED}{NIR+RED}$	0.22–0.95	(Rouse et al. 1974)
Sentinel 2 Normalized difference red edge index	NDRE	$\frac{NIR-REDEDGE}{NIR+REDEDGE}$	0.47–0.84	(Liu et al. 2018)
Soil adjusted vegetation index	SAVI	$(1 + L) \frac{NIR-RED}{NIR+RED+L}$	0.49–0.75	(Huete 1988)
Simple ratio	SR	$\frac{NIR}{RED}$	0.27–0.83	(Jordan 1969)

considered in this study, Table 2 only shows the vegetation indices applied in more than three studies. Most indices were not captured because they were used in less than three studies. Subsequently, the study reports on the sections of the electromagnetic spectrum that have been widely utilized to derive those vegetation indices as in Loris and Damiano (2006), Boschetti, Bocchi, and Alessandro Brivio (2007), Bing and Yuhong (2019), Wang et al. (2019a) and Sibanda et al. (2021).

The widely used sections of the electromagnetic spectrum for the derived vegetation indices were the red and near-infrared regions (NIR). In this regard, the Normalized Difference Vegetation Index (NDVI) was utilized in 65% of the studies, the Enhanced vegetation index (EVI) in 13%, the Soil adjusted vegetation index (SAVI) in 10%, and the Simple Ratio (SR) in 6% of the studies. A considerable number of studies (6%) used red-edge-based vegetation indices, which are calculated based on the red-edge region of the electromagnetic spectrum (Filho et al. 2020). Although most studies used vegetation indices, the results of this review showed that about 8% of the studies assessed the utility of topographic indices derived from DEM in predicting and estimating grassland ecosystem services.

In terms of water-related ES, the used sensors were COSMO-SkyMed, RADARSAT-2, MERIS, MODIS, Sentinel 2, SPOT, TerraSAR-X, Landsat fleet and hand-held spectral devices. Vegetation indices utilized in these studies were Soil Adjusted Total Vegetation Index (SATVI), NDVI and SR. Additionally, red-edge, NIR, and short-wave infrared (SWIR) bands were reported to be critical in characterizing water-related ES. Moreover, only three studies (Bertoldi et al. 2014; Saatchi, van Zyl, and Asrar 1995; Sibanda et al. 2021) used topographic indices in estimating water-related ES.

G = gain factor; C1, C2 = coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol resistance term; L = soil brightness correction factor (Liu and Huete 1995).

3.2.4 The role of remote sensing prediction and modelling algorithms in grassland ecosystem services

Results of this review show that there are 37 algorithms that have been utilized in studying grasslands ES. These thirty-seven algorithms fall into three categories that are as follows:

(1) production efficiency models (n = 18)
(2) machine learning algorithms (n = 10)
(3) multivariate analysis techniques (n = 9)

Figure 9a shows the average coefficient of determination accuracies of production-efficiency models that were used in more than three studies. Fifteen of the 18 production efficiency models were excluded from Figure 9a as they were used in less than three studies (Table 3A: Appendix). The included models yielded high average R^2s ranging from 60.6% to 72.8% (Figure 9a). Results of this study show that PROSAIL was the most widely used model among the production efficiency models. Results also show that light use efficiency (LUE) models are utilized in estimating ecosystem primary production services. For LUE and Carnegie–Ames–Stanford approach (CASA), it was observed that the major inputs for the models were a fraction of Photosynthetic Active Radiation (fPAR) derived from remote sensing data and meteorological data.

Figure 9b shows the average coefficient of determination accuracies of three widely used machine-learning algorithms. Seven of the algorithms were excluded from Figure 9b because they were applied in less than three studies (Table 3A: Appendix). The average R^2s of the algorithms ranged from 64.5% to 75%, showing considerable high prediction accuracies across all the algorithms used in estimating grassland ES. Random forest (RF) had the highest average prediction accuracy (75%) followed by artificial neural networks (ANN) and support vector machines (SVM) with average accuracies of 68% and 64.5%,
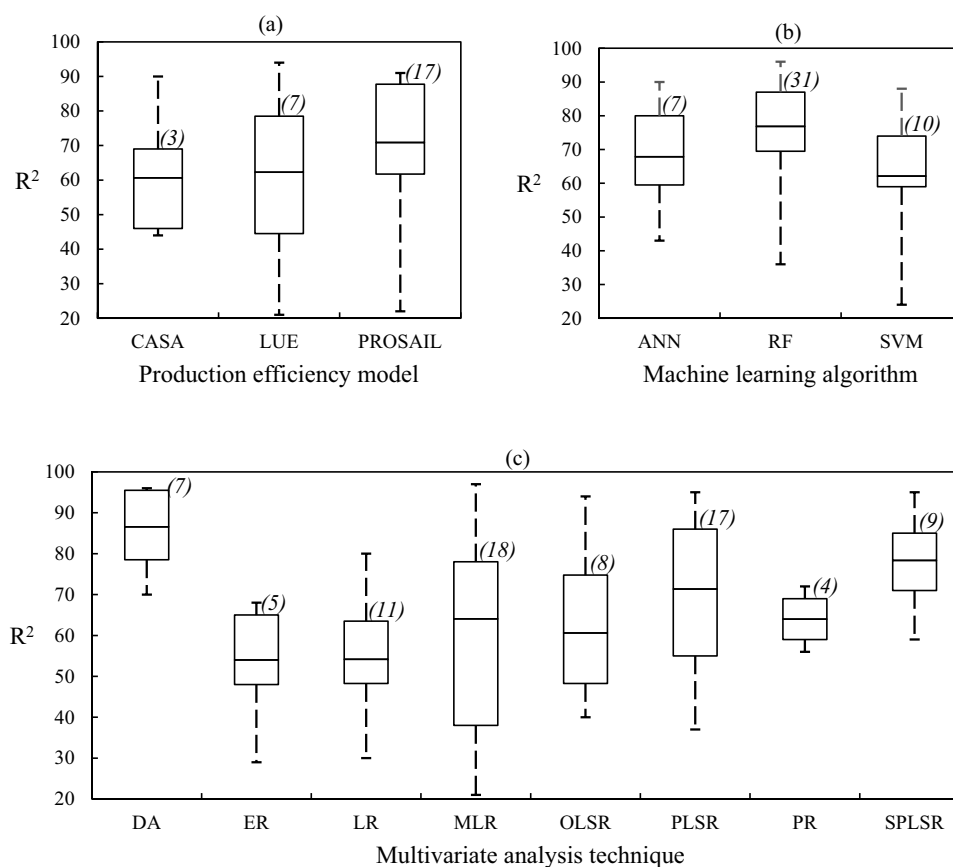
Figure 9. Box plots showing average coefficient of determination (R^2) values produced by remote sensing algorithms applied in the studies. Numbers in italics represent the number of times an algorithm was utilized. (a) CASA = Carnegie-Ames-Stanford Approach; LUE = light use efficiency; PROSAIL = prospect + sail, (b) ANN = artificial neural networks; RF = random forest; SVM = support vector machines, (c) DA = discriminant analysis; ER = exponential regression; LR = linear regression; MLR = multiple linear regression; OLSR = ordinary least square regression; PLSR = partial least square regression; PR = power regression; SPLSR = sparse partial least square regression.

respectively. These algorithms were detected using the network analysis in Figure 2 (green cluster) as topical elements of grassland ES mapping. Meanwhile, multivariate analysis techniques reported in most studies are illustrated in Figure 9c. The R^2 average accuracies ranged from 54% to 86.5%, indicating high model prediction accuracies (Richter et al. 2012). Discriminant analysis (DA) had the highest average prediction accuracy (86.5%) followed by sparse partial least square regression (SPLSR) and partial least square regression (PLSR) with average accuracies of 78% and 71%, respectively. Exponential regression had the lowest average prediction accuracy of 54%.

Algorithms reported in studies that focused on water-related ES include hydrological models (Soil-vegetation-atmosphere transfer (SVAT), Water

cloud, Process-based model, NOAH Land Surface Model (LSM), Rangeland Hydrology and Erosion Model (RHEM), Two Source Energy Balance Atmosphere Land Exchange Inverse (TSEB ALEXI), GEOTop and BROOK90 models), ordinary least square regression (OLSR), linear regression (LR), SPLSR and RF. However, most of these models are excluded from Figure 9 analysis because they were applied in less than three studies (Table 3A: Appendix). Overall, it was observed that the majority of multivariate techniques and machine learning algorithms (i.e. RF, SVM, ANN, PLSR, and OLSR) performed well in literature considered in this study. Also, it was observed that they had a feature selection capability for identifying the most influential spectral features for estimating grass biophysical parameters.

4. Discussion

4.1 Progress in remote sensing of grassland ecosystem services

4.1.1 Geographic distribution and publication trends
Results of this study showed that most grassland ES were conducted in China. This could be explained by the fact that China possesses vast grassland ecosystems that include alpine steppe, meadow steppe, desert steppe, and typical steppe which accounts for 10% of the total grasslands area (Dai et al. 2016). Additionally, China has experienced relative scientific advancement of ecological science and technology (Jun et al. 2020). As an example, China designed and launched environmental and disaster monitoring HJ-1 satellites. Such datasets have become operational in ecological monitoring, including grassland ecosystems (Xing et al. 2014; Meng et al. 2017).

On the other hand, results also showed considerable gaps in the spatial distribution of published articles in Africa, Australia, and South America. This is an interesting finding contrary to the notion that large areas in these continents are covered with tropical grasslands (Lehmann et al. 2011). Overall, it was observed that studies on remote sensing of grassland ES are significantly increasing (Figure 5). Remote sensing technologies have rapidly developed, providing grassland researchers with multi-source and multi-platform remotely sensed data (Tong et al. 2021). Additionally, remote sensing provides the possibility of complimenting ground truth data through remote sensing inversion and data assimilation (Tong et al. 2021). This could possibly explain the increase in grassland remote sensing ES research.

4.1.2 Earth observation sensors
Results in this study showed that MODIS and the Landsat fleet had the highest utilization frequency. Soubry et al. (2021) also noted an extensive utilization of data from the MODIS and Landsat sensors fleets in grassland remote sensing research. The high utilization frequency of such sensors could be attributed to the fact that until recently, Earth observation imagery has been dominated by traditional optical sensors such as MODIS and Landsat (Thenkabail, Smith, and De Pauw 2002). Such sensors have been in orbit for the longest time, and they have global coverage, consistently supplying researchers with freely available remotely sensed imagery suitable for retrieving grass biophysical parameters. Meanwhile, the results of this study also showed that a significant number of studies have explored the utilization of handheld hyperspectral devices. These findings are similar to those of Soubry et al. (2021) who also noted a significant number of studies (16.5%) that were conducted based on hyperspectral sensors. Such sensors provide a wide range of sections of the electromagnetic spectrum in relation to other sensors (i.e. Landsat and MODIS), hence they provide higher, and optimal accuracies in estimating and mapping biophysical and optical properties of vegetation (Cerasoli et al. 2018). In this regard, the use of in situ hyperspectral sensors has the potential of minimizing several errors since data is acquired proximal to the canopy when compared to satellite and airborne sensors (Agapiou, Hadjimitsis, and Alexakis 2012).

Results showed that the application of remote sensing technologies in grassland ecosystems draws back to the 1980s. Initially, this era was associated with aerial photography (Dancy, Webster, and Abel 1986). The changes in remote sensing techniques from aerial images to satellite-borne sensors have achieved a significant advancement in the grassland ES research community. Specifically, the launch of MODIS in 2000 marked a shift within the remote sensing field which may probably explain the constant frequency in the publications on grassland ES occurring in the 2000s decade (Kawamura et al. 2005; Fei et al. 2013; Yu et al. 2021). More so, recent advancements in Earth observation sensors include the launching of Sentinel 2 MSI and the Landsat 8 OLI, offering data on free access policy. With such advancements, the number of studies on mapping and monitoring grassland ES has increased along with the associated accuracies.

A considerable number of studies explored the possibility of using SAR sensors in estimating grassland ES; especially those related to water. SAR has several advantages which include an all-weather capability, independence from solar energy and the ability to select an appropriate wavelength for studying belowground properties and soil substrates (Holmes 1992). Furthermore, changes in vegetation and soil moisture contents contribute to the total backscattered radar signal which influences the absorption, transmission, and reflection of microwave energy (Wang, Linlin Ge, and Xiaojing Li 2013; Xing et al. 2014). Being active sensors, acquiring data in all

weather conditions and being sensitive to vegetation and soil moisture content explains their prospective utility in assessing water-related ES.

4.1.3 Spectral features (wavebands and vegetation indices)

This review highlights that the widely used vegetation indices relied on near-infrared and red bands with NDVI being the widely used index. NDVI is calculated through a normalization procedure using spectral reflectance from the red and the near-infrared bands, which makes it simple to assess vegetation health and vigor (Xue and Baofeng 2017). Despite the wide application of NDVI, it is sensitive to atmospheric effects, leaf canopy, soil brightness, and cloud shadow (Thenkabail, Smith, and De Pauw 2000; Xue and Baofeng 2017). As a result, SR, EVI and SAVI have been proposed to reduce noise effects from non-vegetation matter (Zhengxing, Chuang, and Alfredo 2003; Xue and Baofeng 2017). The application of such indices has greatly promoted the prediction of ES such as forage provision (Kawamura et al. 2005) and primary production (Zhou et al. 2014).

Additionally, the advent of Sentinel 2 MSI offers fine spatial and robust spectral resolution covering the red-edge section of the electromagnetic spectrum. This section is very important for characterizing vegetation attributes (Boochs et al. 1990; Curran, Dungan, and Gholz 1990; Ruiliang et al. 2003; Mutanga and Skidmore 2007; Sibanda et al. 2019). In several studies (Ramoelo et al. 2015; Tong and Yuhong 2017; Munyati, Balzter, and Economon 2020), indices that utilized wavelengths from the red-edge region (i.e. NDRE) performed well in estimating grassland ES as compared to the normal broadband indices (i.e. NDVI), especially in relation to characterizing water-related ecosystems (Sibanda et al. 2021). The reflectance in the red-edge (680–780 nm) provides information on the rapid rise of vegetation reflectance at 680 nm with the highest absorption occurring at 780 nm which better estimates vegetation pigment, physical and chemical parameters (Gao et al. 2019). As such, red-edge-based indices have been suggested to effectively correct variations caused by atmospheric influence, bidirectional reflectance distribution function and background noise (Tong and Yuhong 2017).

4.1.4 Prediction, modeling, and classification algorithms

In terms of remote sensing algorithms, the use of multivariate analysis techniques in grassland ES has been widely reported (Sakowska, Juszczak, and Gianelle 2016; Pang et al. 2020). Multivariate analysis techniques were the most widely used algorithms probably because of their simplicity and ease of implementation. However, multivariate techniques are generally associated with data assumptions, which are not always easy to attain based on ecological data (Finch 2005). For instance, to utilize multivariate techniques data has to meet the assumptions of normality and homogeneous covariance matrices. Meanwhile, Arjasakusuma, Swahyu Kusuma, and Phinn (2020) illustrated that multivariate techniques are susceptible to high data dimensionality and noted that they tend to overfit the models, which reduce the model accuracies.

More research has also been conducted based on machine learning algorithms (Gao et al. 2020; Lehnert et al. 2015; Mutanga and Skidmore 2004). The successful application of machine learning algorithms can be explained by the notion that they are non-parametric and therefore do not rely on any assumptions about data distribution (Barrett et al. 2014). In this regard, they are insensitive to overfitting and could be the best option for modeling grasslands biophysical parameters (Cawley and Talbot 2010). Overall, the majority of the multivariate and the machine learning algorithms showed optimal performance in estimating grassland ES mainly due to their feature selection capability. In this regard, the development of accurate remote sensing models for predicting grass biophysical parameters seems to largely depend on the algorithm used in selecting optimal spectral features from remotely sensed data as noted by Verrelst et al. (2019) and Richter et al. (2012).

Results of this study also showed that production efficiency models are prominent for monitoring ES such as primary production (Propastin et al. 2012; Zhang et al. 2016). A review by Reinermann, Asam, and Kuenzer (2020) also showed that most studies used CASA, LUE, and PROSAIL modeling approaches in analyzing grassland production traits and management. Most of the production efficiency models take into consideration the LUE theory which states that there is a constant relationship between photosynthetic carbon

uptake and radiation interception at the plant canopy level (Monteith 1972; Anderson et al. 2000). Results also showed that the major input for these models is fraction of photosynthetically active radiation (fPAR). This can be explained by the notion that production efficiency models require inputs of meteorological data and satellite Earth observation derived fPAR in order to simulate the total primary production (McCallum et al. 2009). The integration of remote sensing and production efficiency models represents an important approach for monitoring terrestrial carbon exchange across a wide range of spatial and temporal scales. The high average prediction accuracies obtained from these production efficiency models imply that they all exhibit robust techniques to evaluate remote sensing data that can effectively quantify and map grassland ES.

4.2 Remote sensing of biomass, LAI, and CSC to characterize water-related grassland ecosystem services

Results of this present study have shown that various remote sensing technologies have been widely applied in characterizing ES such as forage provision, genetic resource, climate regulation, natural hazard regulation, primary production, nutrient cycling, and habitat support. However, very few studies were noted that sought to understand the role of remote sensing in characterizing biomass, LAI and CSC in relation to water-related ecosystems services management.

Results in this study showed that only three studies evaluated the utility of remotely sensed data in mapping the grass moisture content elements related to biomass. There is paucity of literature that directly focus on the role of remote sensing in estimating grass biomass in relation to water resources despite the fact that grass prevalence has a considerable effect on some hydrological elements. For instance, dense biomass coverage has a direct impact on grass and soil water-holding capacity through induced infiltration (Duley and Domingo 1949). This promotes soil water availability, groundwater restoration, and surface water balance within grassland biomes.

Meanwhile, results showed that few studies have sought to utilize LAI in the context of estimating evapotranspiration. Remote sensing provides spatial and temporal estimations of LAI which can be coupled with meteorological variables in hydrological modeling mostly in evapotranspiration processes (Tesemma

et al. 2015; Rong et al. 2018). Evapotranspiration is the combination of two ecohydrological processes which are plant-mediated transpiration and evaporation (soil surface evaporation and evaporation of rainfall intercepted by plant canopies) (Smallman and Williams 2019). As such, it is a crucial terrestrial component of the hydrological cycle which impacts the magnitude of surface water and variability of catchment water yield and ultimately water balance (Zhang et al. 2008). Although LAI is a critical variable in evapotranspiration, it should be noted that it is also an important structural parameter driving biophysical processes such as transpiration and precipitation interception which in turn influence hydrological processes such as the provision of water by stream flow, superficial runoff as well as the absolute water balance (Boussetta et al. 2013; Zhenwang et al. 2016).

Results showed that two studies (Yu et al. 2012; Sibanda et al. 2021) utilized remote sensing methods to understand the impact of CSC on the hydrological cycle. CSC is an important attribute in controlling actual canopy interception which determines the amount of water reaching the ground (Ochoa-Sánchez, Crespo, and Célleri 2018). It is an important component of the water balance influencing hydrological processes such as run-off, erosion, infiltration, and flood generation (Tsiko et al. 2012). An understanding of such hydrological processes is crucial in understanding water redistribution within grassland ecosystems, which is important for water management. Additionally, CSC is a prominent variable that depends on various canopy structural parameters including biomass and LAI (Xiong et al. 2021). The dense canopy coverage of grasslands biomass means high LAI which reduces surface run-off, thus leading to aquifer water recharge, water flow regulation and balance amongst other elements.

Results in this study show that there are very few studies that considered the utility of DEM derived topographic metrics in estimating water-related grassland ES. DEM provide eco-hydrological information on the profile of the terrain regarding its direct impact on nutrient resources and moisture availability for plants, its impact on hydrological components such as runoff percolation and how these variables interact with each other (Lukyanchuk, Kovalchuk, and Pidkova 2020). The work by Sibanda et al. (2021) concluded that topographic variables such as Topographic Wetness Index, maximum curvature, and aspect were important in characterizing

eco-hydrological proxies such as LAI and CSC that are associated with hydrological ES. There is, therefore, a need for more research efforts to be exerted toward understanding the impact and contribution of topographic variables in mapping and monitoring water-related grassland ES using remotely sensed data.

4.3 Limitation of the study

In conducting the literature search, some studies were unavailable in full length, and others were not written in English. This may have a negative effect on quantifying all the studies which focus on grassland ES. More so, the exclusion of these studies has an impact on the spatial distribution of grassland ES studies.

The fundamental basis of utilizing remote sensing technologies is based on their reliability to provide accurate spatially explicit information. This implies that accuracy assessment and validation of remotely sensed data is essential for decision-making and sustainable ecosystem monitoring. However, in this study R^2 was used as an indicator of prediction accuracy since other accuracy assessment measures are based on different SI units of measurement. It is important to note that R^2 is one performance value amongst other parameters such as RMSE, relative room mean square error (RRMSE), standard error of prediction (SEP). It also must be outlined that R^2 assesses the goodness-of-model fit. Furthermore, accuracy assessment parameters associated with remotely sensed data models, inclusive of R^2, are impacted by many factors that include data sample size, sampling techniques, sensor type, vegetation indices or modeling approach being applied. That needs to be also considered in interpreting and contextualizing the findings of this study.

Considering that we intended to explore whether there were generally significant differences in the accuracies derived using different sensors, algorithms, or vegetation indices, we assumed that the international peer review system followed by each of the journals considered in this study was sufficient and robust in evaluating the credibility and verification of the accuracies presented in each article.

4.4 Research gaps and opportunities

The following gaps and opportunities have been identified from the results of this study in the context of applications of remote sensing technologies in grassland ES studies:

- Considerable gaps still exist around the world and more specifically in the African continent on the integration of remote sensing into grassland ES.
- Grasslands provide more ES than the ones stated in this review. For instance, grasslands offer ES that are related to the hydrological cycle such as the canopy storage capacity, facilitation of infiltration and underground water storage refills. There is a paucity of literature on the application of Earth observation data in quantifying the full range of such grassland ES. Meanwhile, some of these ES such as CSC that are related to LAI, can be characterized using remotely sensed data. LAI is arguably the most important vegetation structural parameter responsible for water and carbon exchange of vegetated land surfaces. Spatial distribution of LAI has an impact on the total water interception by plant canopy, which directly influence plant CSC. Remotely sensed LAI and CSC data combined with remote sensing algorithms have a clear advantage of modeling eco-hydrological processes (evapotranspiration, run-off, precipitation interception, surface water variability) which are crucial for understanding water balance within grasslands
- The application of remote sensing technologies for estimating biomass in relation to water management has not attracted significant attention from the research community. Remote sensing-based modeling can be a useful tool for large-scale prediction or estimation of surface water supply within grasslands. Remotely sensed biomass data can be used as an input in hydrological models. Such data can be simulated with run-off datasets to predict surface water supply.
- Erosion regulation can be estimated using remote sensing-based vegetation indices such as modified normalized vegetation index (mNDVI), normalized difference soil index (NDSI) and tasseled cap transformation (TCT) based vegetation

indices. These indices are frequently used to investigate soil exposure, assess soil properties, and estimate soil erosion processes (Xu et al. 2019).

- There is a paucity on studies that have sought to evaluate the influence of variations in topographic metrics on water-related grass ES. The integration of vegetation indices and topographic metrics may provide robust models capable of predicting water-related grasslands ES especially at local scales.
- Integration of remote-sensing data and public participation geographic information systems (PPGIS) may be useful for quantitative evaluation of cultural services offered by grasslands. PPGIS pertains to the use of geographic information systems to produce local knowledge with the goal of including and empowering marginalized populations (Brown, Montag, and Lyon 2012). Remote sensing of land use/land cover changes and local spatial knowledge may help in understanding how social and ecological systems are interacting over time. Also, PPGIS may help integrate people's cultural values to grassland ecosystems. The capabilities of PPGIS have been successfully implemented to assess ES provided by wetlands (Loc et al. 2021) and protected forests (Peng et al. 2019).
- There is also a need to consider the impact on newly launched sensors such as Landsat 9 OLI in characterizing water-related grasslands ES.

5. Conclusion

The objective of this study was to conduct a systematic review of literature, specifically assessing progress, identifying research gaps and opportunities on the application of remote sensing technologies in quantifying grassland ecosystem services, with particular attention to water-related services. Nine-grasslands ecosystem services were mentioned in the reviewed studies with forage provision, climate regulation, and primary production having the highest frequencies. Over the past decade, grassland ES studies have experienced exponential growth, reaching a total of 222 published articles in September 2021. The results show that the integration of remote sensing technologies into grassland ES has been well incorporated. This is explained by the ability of Earth observation sensorsystems, vegetation indices, and remote sensing algorithms to quantify and map several ES with

considerable high prediction accuracies. Grass biophysical parameters such as biomass, LAI and CSC are prominent attributes for understanding hydrological processes and water balance within grasslands. The remote-sensing-based estimation of such parameters in relation to water management is still in infancy. In this regard, there is room for more research efforts in understanding their effective contribution to the hydrological cycle which is important in water management.

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Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Appendix

Table 3A. Additional remote sensing algorithms applied in the studies.

	Algorithm	Application	Results	Reference
Machine learning Algorithms	Adaptive neuro-fuzzy inference system (ANFIS)	Grassland yield estimation	$R^2 = 0.86$ & RMSE = 11.07 kgDM/ha	(Ali et al. 2014)
	Extremely randomized trees (ETR)	Classifying grassland types	OA ˃ 87.4 % Kappa ˃ 85%	(Barrett et al. 2014)
	Classification and regression trees	Species distribution modelling	OA = 90.62 % Kappa = 79.07 %	(De Simone et al. 2021)
	Cubist regression trees	Canopy cover Aboveground biomass	$R^2 = 0.67$ & RMSE = 14.4 % $R^2 = 0.68$ & RMSE = 76.9 g m-2	(John et al. 2018)
	Stochastic gradient boosting	Grass nutrients	R^2 range of 0.65–0.72 RMSE range of 2.42 to 3.11 % DM	(Singh et al. 2018)
	Decision trees	Pasture productivity	90.9 % prediction accuracy	(Zhang et al. 2006)
	High-Accuracy-Surface-modelling (HASM)	Aboveground biomass	$R^2 = 0.8459$ & RMSE = 29 g/m^2	(Zhou et al. 2021)
Production Efficiency models	Alpine vegetation model (AVM)	GPP	$R^2 = 0.857$ & Conversion coefficient 19.91 g C m^{-2}	(Fei et al. 2013)
	Vegetation photosynthesis model (VPM)	GPP	GPP predicted relative error range 1.4 to 7.4 %	(Zhengquan et al. 2007)
	MODIS MOD 17 Net Primary Production Product	Aboveground NPP	Average NPP = 2163 kg ha^{-1} (paired t-test, t = 2.43, d.f. = 16, $P_{2\text{-sided}}$ = 0.027).	(De Leeuw et al. 2019)
	Soil-leaf-canopy radiative transfer model	LAI BIOMASS	$R^2 = 78\%$ & NRMSE = 30% $R^2 = 90\%$ & NRMSE = 47 %	(Schwieder et al. 2020)
	Plant canopy mortality model	Biomass carbon storage Carbon density	4.95Tg, 4.53Tg, 4.80Tg (1Tg = 1 × 1012 g) in 2002, 2005 and 2009 43.41 g/m2, 39.69 g/m2, 41.36 g/m2 respectively in 2002, 2005 and 2009.	(Chen, Wu, and Qing 2015)
	Canopy height model	Canopy height Aboveground biomass	$R^2 = 0.90$, RMSE = 19.79 cm & rRMSE = 16.5%, $p < 0.001$) $R^2 = 0.89$, RMSE = 91.48 g/m^2, rRMSE = 16.11%, $p < 0.001$)	(Zhang et al. 2018)
	MODIS GPP	GPP	Mean GPP = 353 and 375 g C m^{-2} for 2000 & 2001 respectively	(Zhang et al. 2007)
	Piecewise regression GPP	GPP	$r = 0.82$–0.98 and $d = 0.71$–0.97 cross validation with tower-based GPP mean GPP = 402 and 431 g C m^{-2} for 2001 and 2001	(Zhang et al. 2007)
	Biome BGC	GPP	$R^2 = 0.94$ & RMSE = 0.95 gC/m^2/da $R^2 = 0.83$ & RMSE = 0.48 gC/m^2/da $R^2 = 0.68$ & RMSE = 1.66 gC/m^2/da	(You et al. 2019)
	GLOPEM-CEVSA	NPP	Adjusted $R^2 = 0.80$ (p < 0.01).	(Ye et al. 2019)
	Defoliation formulation model	NPP	Annual NPP predicted between 1982–2011 = 179.41 gC·m-2 yr-1. Increase rate per time period 1.18 gC·m-2 yr-1 (Adjusted $R^2 = 0.63$, p < 0.01)	(Ye et al. 2019)
	Bayesian model data fusion (MDF)	Biomass Carbon balance	$r = 87.5\%$ (biomass harvest) $r = 83$ % (biomass annual yields) $r = 0.80$ overlap = 90% (grazing intensity)	(Myrgiotis et al. 2021)

(*Continued*)

Table 3A. (Continued).

	Algorithm	Application	Results	Reference
	LINGRA	Grass yield	Average normalized error between observed and predicted: 14 % for irrigated grass 19 % for non-irrigated grass	(Schapendonk et al. 1998)
	Boreal Ecosystem Productivity Simulator (BEPS)	NPP GPP	Total NPP = 2.235 GtC Mean NPP = 235.2 gC m^{-2} yr^{-1} Total GPP = 4.418 GtC Mean GPP = 465 gC m^{-2} yr^{-1}	(Feng et al. 2007)
	Improved Solar-energy efficiency	NPP	Total NPP = 2.9×10^{13} gC/a in 2006, with an average of 261.01gC/m^2·a.	(Wang and Wei Yang 2012)
Multivariant analysis techniques	Principal Component regression	Biomass	$R^2 = 0.31$ & RMSE = 2.48 g/m^2	(Darvishzadeh et al. 2014)
Hydrological models	Soil-vegetation-atmosphere transfer (SVAT)	Canopy evapotranspiration Transpiration	Correlation between ET measured from Eddy covariance method and SVAT ($r^2 = 0.85$; ET-SVAT = 0.91 × ET-Eddy + 0.05). 5 July = (0.39 × LAI + 4.3, $r^2 = 0.64$, $P < 0.001$ 31 July = (0.15 × LAI + 4.0, $r^2 = 0.32$, $P < 0.001$).	(Shimoda and Oikawa 2008)
	BROOK90	Evapotranspiration	Explained model variance range $R^2 = 0.54$–0.98 Nash–Sutcliffe model efficiency (E_{NS}) range = 0.53–0.82	(Vetter, Schaffrath, and Bernhofer 2012)
	BROOK90	Evapotranspiration	BROOK90 mean coefficient of variance (CV) range = 25%-75%. Correlation between BROOK 90 and MODIS evapotranspiration data $R^2 = 0.63$, n = 160	(Schaffrath and Bernhofer 2013)
	Rangeland Hydrology and Erosion Model (RHEM)	Rainfall fun-off	Total run-off volume R^2 range = 0.53 to 0.54 & PBIAS % range = −50.33 to −113.27 Peak run-off R^2 range = 0.50 to 0.53 & PBIAS % range = −2.71 to − 56.56.	(Kautz et al. 2019)
	Two Source Energy Balance Atmosphere Land Exchange Inverse (TSEB ALEXI)	Evapotranspiration	TSEB RMSE = 0.421 mm day^{-1} DisALEXI MOD RMSE = 1.877 mm day^{-1} DisALEXI MOD vs TSEB RMSE = 1.75 mm day^{-1}	(Castelli et al. 2018)
	NOAH Land Surface Model	Soil moisture Evapotranspiration Energy balance components	Predicted soil moisture range = 3–25Vol.% & Root zone moisture = 60–120 mm Predicted ET range = 0 mm-75 mm Predicted energy balance range = −10 – 150 MJ/m^2/day	(Sridhar and Wedin 2009)
	Water cloud model	Soil moisture	RMSE = 4.7 & 7.5 Vol.% Bias = 0.7 & −0.4Vol.%	(El Hajj et al. 2015)
	Water cloud model	Soil moisture	$R^2 = 0.7075$, RMSE = 3.3219 m^2 /m^2).	(Xing et al. 2014)
	GEOTop Hydrological model	Soil moisture content	$R^2 = 0.2$, RMSE = 0.13 m^3/m^3 & bias = −0.02 m^3/m^3	(Bertoldi et al. 2014)
	Process based models	Water productivity	R^2 range = 66.5–75.3 &Water productivity estimate range = 11.8–42.6 kg ha^{-1} mm^{-1}.	(Aiming, Murray, and Richter 2017)