remote sensing

Review

Advancing Skyborne Technologies and High-Resolution Satellites for Pasture Monitoring and Improved Management: A Review

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Abstract: The timely and accurate quantification of grassland biomass is a prerequisite for sustainable grazing management. With advances in artificial intelligence, the launch of new satellites, and perceived efficiency gains in the time and cost of the quantification of remote methods, there has been growing interest in using satellite imagery and machine learning to quantify pastures at the field scale. Here, we systematically reviewed 214 journal articles published between 1991 to 2021 to determine how vegetation indices derived from satellite imagery impacted the type and quantification of pasture indicators. We reveal that previous studies have been limited by highly spatiotemporal satellite imagery and prognostic analytics. While the number of studies on pasture classification, degradation, productivity, and management has increased exponentially over the last five years, the majority of vegetation parameters have been derived from satellite imagery using simple linear regression approaches, which, as a corollary, often result in site-specific parameterization that become spurious when extrapolated to new sites or production systems. Few studies have successfully invoked machine learning as retrievals to understand the relationship between image patterns and accurately quantify the biophysical variables, although many studies have purported to do so. Satellite imagery has contributed to the ability to quantify pasture indicators but has faced the barrier of monitoring at the paddock/field scale (20 hectares or less) due to (1) low sensor (coarse pixel) resolution, (2) infrequent satellite passes, with visibility in many locations often constrained by cloud cover, and (3) the prohibitive cost of accessing fine-resolution imagery. These issues are perhaps a reflection of historical efforts, which have been directed at the continental or global scales, rather than at the field level. Indeed, we found less than 20 studies that quantified pasture biomass at pixel resolutions of less than 50 hectares. As such, the use of remote sensing technologies by agricultural practitioners has been relatively low compared with the adoption of physical agronomic interventions (such as 'no-till' practices). We contend that (1) considerable opportunity for advancement may lie in fusing optical and radar imagery or hybrid imagery through the combination of optical sensors, (2) there is a greater accessibility of satellite imagery for research, teaching, and education, and (3) developers who understand the value proposition of satellite imagery to end users will collectively fast track the advancement and uptake of remote sensing applications in agriculture.

Keywords: AI; end user; grassland management; land-use; machine learning; pasture biomass; satellite; species composition; sustainability; unmanned aerial vehicle

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1. Introduction

Pasture ecosystems transverse more than 40% of earth land surfaces [1], supporting a broad range of biodiversity, conservation, and environmental sustainability [2,3] while making substantial contributions to global carbon removal [4,5]. Globally, the livestock industry directly supports the livelihoods of over 1 billion households, particularly in developing countries, where the pastoral system underpins food security [6,7], often because grasslands are the least expensive form of feed and one of the few ways that extensive land areas can be used for agri-food production [5].

Herein, we define “pastures” as uncultivated grasslands or rangelands (shrublands, prairies, woodlands, meadows, steppe, and savannas (Figure 1)) subjected to seasonal native and domesticated livestock grazing. Rangelands are not subject to intensive management except for seasonal grazing [8,9], often due to their low productivity as determined by seasonal weather [10]. Other pasture types (e.g., sown or exotic species) may originate through the human cultivation of cleared land or conversion from natural grassland. Natural grassland converted to pasture may exclude farm inputs [9], while intensively managed pastures often are subject to management interventions (mowing, synthetic fertiliser, irrigation, pasture species renovation, fencing, etc) to enhance productivity to provide financial income [11–13]. Grasslands may also serve to produce livestock supplementary feeds, such as hay, silage, and grain [9,14]. Often, pastures are defined based on their global and regional relevance (Figure 1).

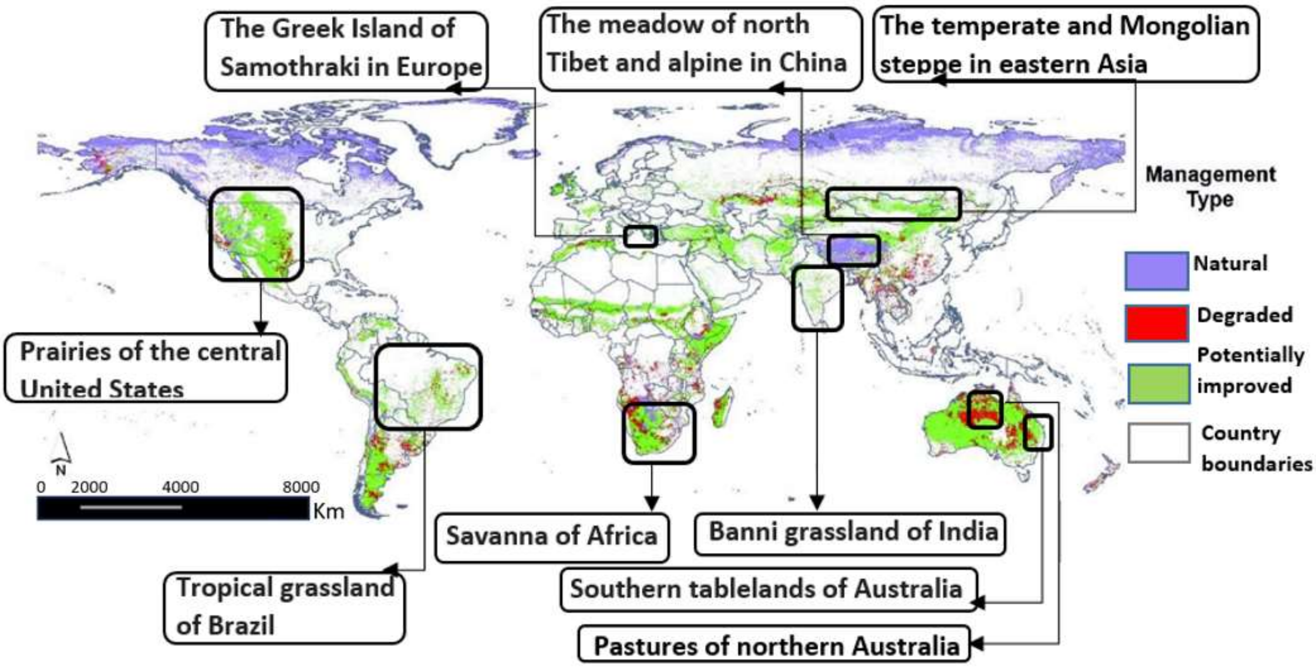

Figure 1. Global distribution of pastures and assessment using remote sensing tools. “Global assessment of land degradation and improvement 1. Identification by remote sensing” (Bai et al., 2008 [15]). Global grassland classification was embellished to the original map by the authors.

Many direct and indirect factors can result in the degradation of pasture ecosystems. These may include overgrazing, the inherent soil structure, adverse climate conditions, competing land-use activities or incursions by noxious weeds and/or feral flora and fauna [16–24]. Decisions to optimise management practices [25] require the support of the efficient and accurate monitoring of production (i.e., quantity), quality, species composition, and availability [4]. Global climate change, including the elevation of temperature and CO_2, will affect pastures, altering the species competition dynamics due to changes in the optimal growth rate [5,26]. The mechanism by which plant functional types (e.g., C3, C4) adapt to environmental stresses or ecological disturbances has been classified into two main features they possess, i.e., structural and functional characteristics [9]. Pasture composition, functioning, and structure can be vulnerable to the harmful effects of climate change and anthropogenic activities (i.e., overgrazing), and when a critical threshold [27–29] is reached, may hit degradation tipping points.

Avenues for monitoring pasture sustainability indicators fall into three broad categories: field techniques, laboratory/greenhouse/allometric analyses, and proximal sensors.

Field techniques to quantify pasture biomass may include (1) visual methods (i.e., field walking and boot height) to estimate grass height, (2) using scientific equipment such as a Rising Plate Meter (RPM) or C-Dax system (a tow-behind device, see www.c-dax.com, accessed on 6 April 2023) to measure the height and density of pastures [3,30], and (3) destructive harvests through quadrat sampling [26]. While such methods provide data on the ground, previous studies have suggested that such methods cannot adequately account for intra-paddock or intra-seasonal variation [31–33].

Laboratory, greenhouse and/or allometric analyses facilitate the direct assessment of morphological parameters such as the leaf area index (LAI) and aboveground biomass (AGB) [34–37]. Forage productivity and quality through the essential structural contents of feed values (e.g., crude protein, green and dry matter, ash, neutral detergent fibre, etc.) can be easily estimated by statistically upscaling [14,38–43]. Although such approaches are accurate and suitable for measuring pasture quality, they are destructive [43,44] and cannot be scaled to larger areas.

Proximal sensing is carried out by equipment such as field spectroradiometers (FieldSpec), ultrasonic sensors, and sonars, with the intent of estimating morphological parameters, e.g., AGB, LAI, sward height, soil moisture, etc., [32,41,45–47] from multispectral wavelengths (i.e., red, blue, green, and near-infrared) [39,48] or hyperspectral reflectance bands (i.e., 10–20 nm). However, the influence of soil and ground reflectance (albedo) can interfere with spectral distinction [41] and introduce errors due to instrumental instability [47]. In addition, intra-paddock pasture composition variability due to grazing management (i.e., stocking rates) may not be adequately quantified with this approach [32,49]. In summary, pasture monitoring using direct or proximal approaches can effectively calibrate ground-based pastures, e.g., biomass estimation and retrievals of biophysical parameters for validation purposes. However, such methods can be time-consuming and/or labour-intensive and are often unsuitable for application over a large area [50].

Like other techniques, remote sensing is susceptible to problems associated with technology limitations (i.e., errors from cloud cover, noise, atmospheric and geometric correction, and radiometric resolution) [51]. Global studies have highlighted the possibilities of using remote sensing to monitor pasture cover and biomass while reducing error rates [52–54]. Most previous work has, however, focused on global, regional, or sub-regional monitoring [55–57]; much less attention has been paid to pasture remote sensing at the farm or paddock level, likely because most remote sensing applications have been at larger scales [33,58]. The emergence of newer satellite constellations (e.g., Sentinel and PlanetScope [59]) could be expected to premise innovation in pasture monitoring at a level that can be carried out at more frequent intervals (1–5 days).

The primary objectives of this paper are to (i) review existing satellite and UAS applications in pasture monitoring; (ii) investigate existing approaches for the management of pasture traits, productivity, botanical composition, and pasture degradation; and (iii) explore barriers to the adoption of satellite driven technology by end users.

2. Methods

We included peer-reviewed papers published from January 1991 to February 2021 and excluded conference proceedings and documents written in languages other than English. We first searched the Scopus database interrogated with the term "remote sensing," which returned 254,392 documents (see Appendix A for the flowchart). We then searched terminology used to describe vegetation under management, i.e., "(pasture* OR grassland* OR rangeland*) management", which returned 31,938 documents. We then combined queries (#1 AND #2), resulting in 1582 documents. We introduced grazing (i.e., graz*) to streamline this third list to select only articles that describe vegetation under a grazing regime, obtaining 633 papers. After eliminating conference papers and proceedings, we obtained 262 articles. We previewed the articles using the search strings described in Table 1, and by reading the abstracts to eliminate unrelated papers, reduced the number of papers to 214. Articles that made the final round (i.e., 214) were grouped into original research and review papers. From these documents, the following information was extracted:

- The geographical location/site of a study.
- The type of sensor used (i.e., optical, multispectral, hyperspectral, SAR).
- Whether a single sensor was used or a combination of sensors together (i.e., fusion).
- The scale with which pasture was monitored (i.e., ≤5 ha, ≥10 ha, ≤50 ha and ≥100 ha);
- The approach for retrieving vegetation parameters for estimating pasture indicators and how this was validated. Information on the adoption of remote sensing approaches by end users.
- Whether environmental (climate and anthropogenic) variables and machine learning were considered.

We exported results using the Research Information System (RIS) tag format by creating a custom CSV file to format and analyse data. We defined "UAS" as unmanned aerial systems remotely controlled or programmed to fly autonomously with onboard high-resolution sensor(s). In contrast, satellites orbit the earth with onboard sensor(s) often lower than UAS in spatial resolution.

Table 1. Search phrases used to refine papers reviewed.

Search Categories	Search Strings/Synonyms/Terms
Pasture Management traits	quality, fertilizer, manure, irrigation, nutrient, management, "soil condition", "water", "mowing"
Pasture Production	quantity, height*, sward, biomass, production, productivity, yield*, growth, "growth rate"
Pasture Composition	species, botanical*, classification,
Pasture Degradation	decline, "grazing intensity", "grazing pressure", "overgrazing", "carrying capacity", "stocking rate", "stocking density", "land use", "fractional cover"
Vegetation	Grassland*, rangeland*, pasture *, graz*
Remote Sensing	"Earth observation", UAS or UAV, drone, satellite*,
Remote Sensing Adoption	"end-user* ", adoption*, technology

3. Results

The major global grasslands where authors use remote sensing technology to study pasture conditions are shown in Figure 1. For example, the Banni grassland in India [60], the temperate [61,62] and Mongolian steppe [28,63,64] in eastern Asia, the prairies of the central United States [45,49,65–68], the meadow of North Tibet [69–71] and alpine in China [72,73], the tropical grassland of Brazil [74,75], the savanna of Africa [7,76,77], the Greek island of Samothraki in Europe [20,78] and the southern tablelands of Australia [79–81] are places of interest where human-induced activities have impacted pasture ecosystems.

3.1. Spatial and Temporal Dimensions of Reviewed Papers

The review process revealed 199 articles from 46 countries (Figure 2), with the United States having the most studies (n = 38; being primarily related to management, production, species composition, and degradation) followed closely by China (n = 36). Asia had a higher proportion of relevant papers (i.e., 24.6%) than other continents due to the publications from China; Australia (n = 16), South Africa (n = 12), Argentina (n = 8), Canada (n = 7), New Zealand (n = 5), Germany (n = 5), Sweden (n = 4), Uruguay (n = 4), Brazil (n = 4), and France (n = 4) had relevant publications.

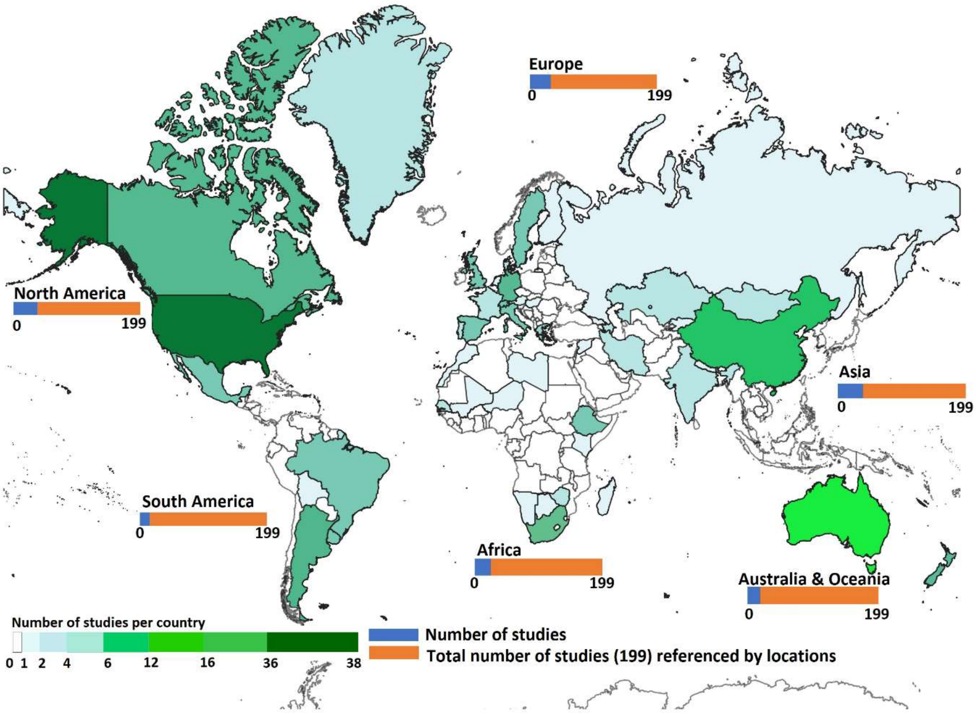

Figure 2. Number of studies from each country and across continents reviewed. Note: the blue and orange colours represent the ratio of the number of studies (blue) compared to the total number of studies (orange).

The number of remote sensing studies was low in 1991, and has increased exponentially. Studies in earlier years focused on management and production, while the proportion of studies on pasture degradation, productivity, and management increased significantly in later years. A lack of publicly available satellites and UAS may have caused fewer studies in the early 1990s. Figure 3 shows the temporal pattern of studies when grouped by management traits, pasture production, species classification and degradation.

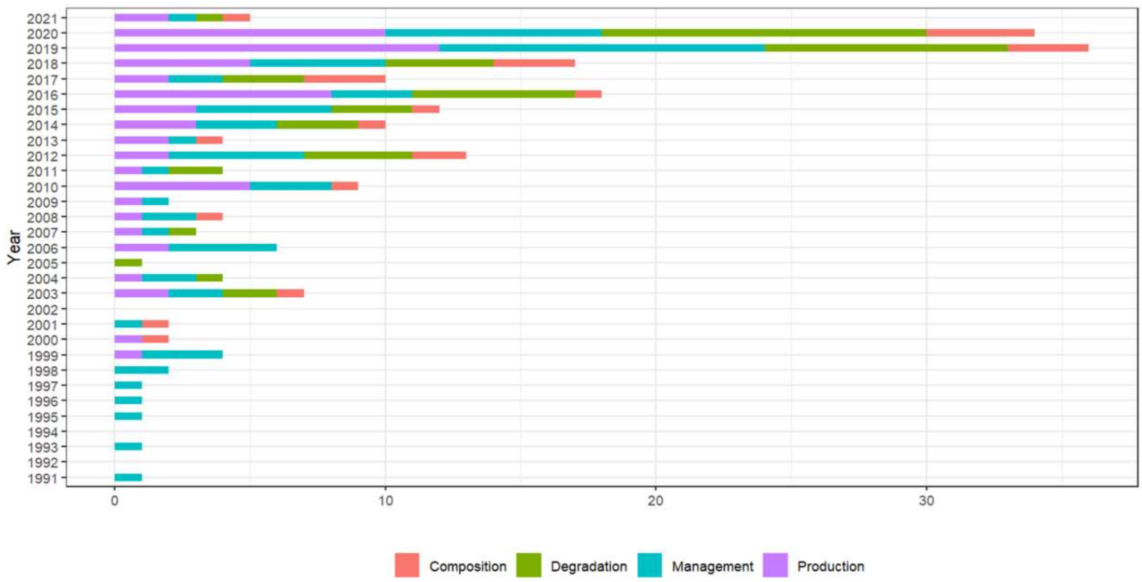

Figure 3. Temporal (annual) pattern of studies reviewed by their topics of coverage. Bars indicate the number of studies published each year.

3.2. Remotely Sensed Environmental Parameters Applied to Pasture Monitoring

Two primary drivers, namely, anthropogenic and climate/weather, influence pasture mapping (production, composition, and degradation) globally (Figure 4a). Anthropogenic factors (referenced by 75 studies) are further categorised to include stocking rate, stocking density, grazing intensity, grazing system, livestock weights, mowing, soil and fire management, land use, pasture treatment (i.e., fertilizer, herbicide, nitrogen, etc.) and irrigation [2,7,49,65,66,80–90]. These variables are quantified through field measurements (and/or ancillary data) and correlated against remote sensing data [50,70].

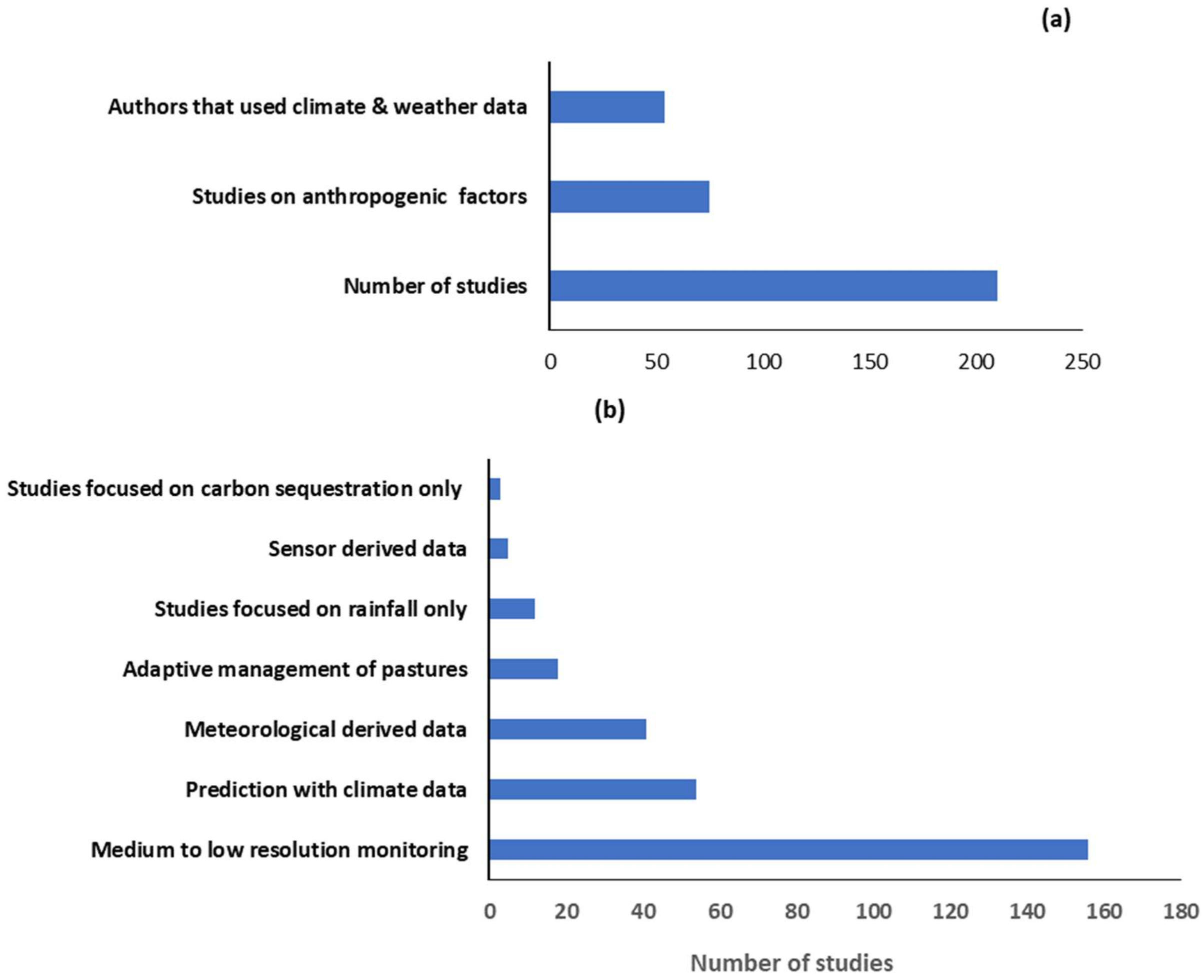

Figure 4. (**a**) The two main drivers of pasture variability, climate, and anthropogenic (**b**) studies using remote sensing to understand how adaptive pasture management could be used to mitigate climate change. Rainfall and temperature variables are regarded as weather and climate data.

Assessing climate or weather's influence on pastures (i.e., mapping pasture phenology) involves (see Figure 4a) correlating climate and weather data with vegetation parameters (i.e., aboveground biomass, ground cover, and canopy cover) [6,35,49,64,66,80,91–95]. Historical time series satellites (Landsat, AVHRR, MODIS) (medium to low sensors) [2,17,19,70,73,84,91,92,94,96–103] are used mainly. Other methods include simulation and modelling approaches to distinguish between human activities and climate [19,84,104–107]. Examples of such modelling approaches include annual unharnessed net primary productivity (NPP) from livestock grazing intensity using a defoliation formulation model (DFM) [107], terrestrial ecosystem model (TEM) (potential) and Carnegie Ames Stanford Approach (CASA) [19].

A total of 54 studies (Figure 4a) used climate and weather data to predict climate's effects on pastures; authors have used climatic data (over at least ten years) and historical time series satellites. Studies focusing on less than ten years were those using a monthly seasonal approach (154 studies) to monitor pastures; we categorised these studies here as "medium to low resolution" (Figure 4b) [49,64,66,80,108–112].

In general, the studies reviewed were conducted using low-spatial-resolution satellite instruments. A few studies used high-spatial-resolution datasets (i.e., Sentinel-2 (four studies), PlanetScope (1 study), QuickBird (1 study)) to understand climate and weather effects on pasture composition [108,113], pasture biomass [3,74,114] and pasture quality [50]. One study invoked a very high temporal time-lapse camera to study the phenology of pasture species at the paddock scale compared with that from the landscape scale using MODIS and Landsat instruments [80]. Only 18 studies considered the adaptive management of pastures with remote sensing strategies [17,21,28,34,67,73,80,94,114–123] (Figure 4b).

Regarding climate data, authors have primarily focused on temperature and rainfall; few have used only temperature [8,90] or rainfall data [91,96,100,106,124–127] to correlate with remote sensing data. Many studies have attempted to establish a correlation between rainfall and the growing season (mostly early and mid-growing season) [35,64,66,70,98,103,128]. Some studies have showed that temperature correlated positively to pasture growth according to the climatic zone (e.g., temperature contributed to growth rates in the desert steppe of Inner Mongolia [64], suggesting the steppe possesses more resilience in this region). Other studies have aimed to elucidate the effects of the climate on soil carbon stocks [113,129,130] and/or the soil water content [63,81]. A significant portion of studies used weather and climate data from meteorological stations (Figure 4b); very few were derived (e.g., groundwater content) from sensors as a proxy and compared with ground measurements (i.e., wet and dry pasture biomass) [76].

3.3. Remote Sensing Technologies Used for Pasture Monitoring

3.3.1. Description of Remote Sensing Technologies Used

A total of 18 sensors from satellites and UAS were reviewed (Figure 5a). Our results show that contemporary scientific capabilities in monitoring pasture dynamics in the past decade are gaining momentum, from satellite and UAS sensors to aerial stereoscopic imagery. Figure 5b categorised sensors using combinations of two optical instruments (OO) or optical and radar instruments (OR) [45,58,87,131]. A greater number of studies used satellites than UAS sensors (Figure 6), and fewer studies used SAR (Synthetic Aperture Radar). The main objective for combining sensors [45,118,132] is to address cloud contamination, especially in places where cloud poses significant challenges (i.e., tropical rainforest, mountain regions, polar and monsoon areas) [32,74,99,133–135], with multi-temporal sensors approach [99,136,137] or by using SAR imagery [7,132,138,139]. Other objectives include comparing model performances between sensors [7,34,45,132,140,141] and when greater detail is needed for field measurements and species discrimination [114,142,143]. Fused data of 30 cm resolution from UAS and PlanetScope imagery achieved a higher correlation of 87% compared with ground measurement for estimating pastures at the field level (10 ha) than those obtained from Planet (65%) data [114].

Moderate Resolution Imaging Spectroradiometer (MODIS) (Terra and Aqua) and Landsat instruments were the most used for studies (Figure 6; Tables 2 and 3). The use of MODIS is enabled by daily revisit, 16-day composite, three spatial and global resolutions (250 m, 500 m, and 1 km), and 36 multispectral bands for wider applications. Long-term data continuity, moderate-resolution imaging, multispectral capabilities, and open data policy (Table 2) are among the factors that have aided Landsat's utility. In general, the use of sensors by practitioners tends to follow their release, accessibility, and applications (Tables 2 and 3).

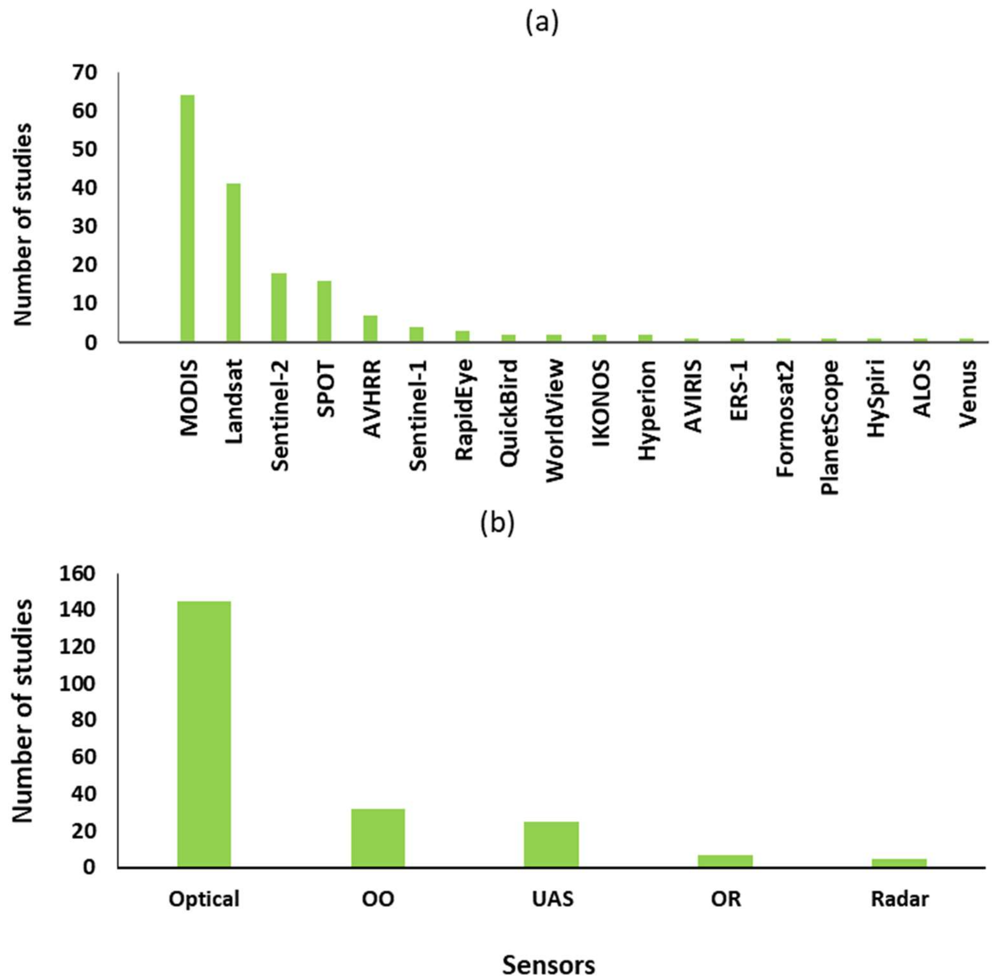

Figure 5. (**a**) Remote sensing instruments to study pasture conditions. (**b**) Number of studies according to how instruments were combined for investigation. OO = combination of optical instruments, OR= combination of optical and radar instruments, and UAS = unmanned aerial systems.

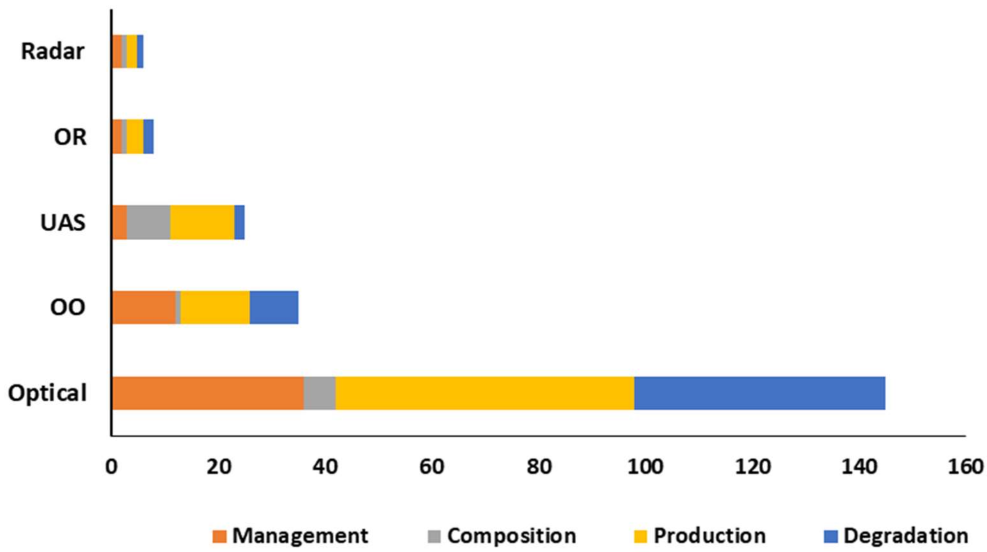

Figure 6. Number of studies ranked by the topics covered: OO = combinational of optical instruments, OR= optical and radar instruments; and UAS = unmanned aerial systems.

Figure 7 shows the areas of coverage and scale of focus for the current monitoring of pasture with satellite sensors. MODIS and Landsat sensors are used primarily to support the regional and global monitoring of pastures at scales ≥100 ha [45,67,103,115,126,144,145]. Figure 8 is an example of hyper-spatial paddock monitoring. Time-series analysis showed that eight studies utilised daily remote sensing data (Figure 9) [58,114,146,147], five focused on weekly [3,126,148–150], while others considered monthly [8,151] and yearly data [92].

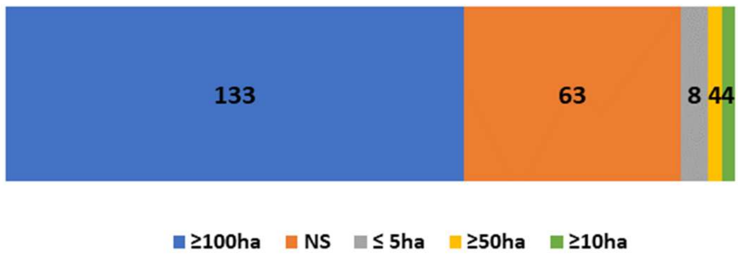

Figure 7. Summary of the scale of focus enabled by satellite sensors. Note: NS = "Not specified" for studies that do not provide a definite statement about the scale of coverage in the reviewed studies. Studies (i.e., 63) indicated study locations without providing details about the scale of focus [76,152–154].

Figure 8. (**a**) A high PlanetScope imagery quantifying pasture biomass variation at paddock level (image acquired from Planet Lab Inc.; and accessed on 6 April 2021); (**b**) was georeferenced from (**a**). Landholders can make management decisions based on pasture availability. (**b**) was georeferenced using the map features provided (i.e., Ngahinapouri, Waipa District, Waikato, 3882, New Zealand).

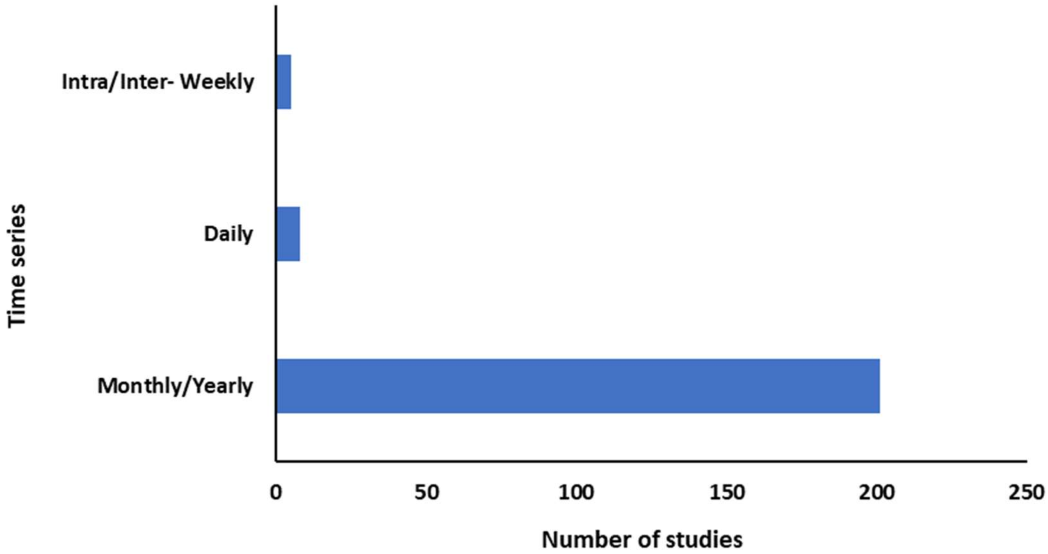

Figure 9. The frequency with which pastures were monitored via satellite imagery passes.

3.3.2. Definition of Pasture Feature Terminologies as Used in the Review

Pasture management traits are the desired indicators for conserving, restoring, and maintaining grassland conditions [12] (Table 1). Pasture production refers to the quantitative parameters that express pasture's dry matter content (kg DM/ha), height, and growth stages (see Table 1). Pasture degradation refers to decreased sward productivity (carrying capacity) due to anthropogenic and environmental activities on pasture ecosystems. Botanical/species composition refers to ground cover types expressed as canopy architecture.

3.4. Approaches for Pasture Quantification

3.4.1. Pasture Production

Studies have used pasture heights [7,116,132,146,150,162,184–186] LAI [32,45,49,66,135,150,164,187], fractional cover (fCOVER) [188], above-ground net primary production (ANPP) (unit mass per unit area per unit time) [8,34,96,111,189,190], fraction of photosynthetic active radiation (fPAR) [191] as quantitative parameters to express pasture production. ANPP and fPAR are mainly derived from Landsat and MODIS time-series products to quantify the managed ecosystem productivity, making them less applicable compared to LAI and pasture heights. Studies have compared pasture biomass with LAI [32,45,49,119,188,191] and height [132,150,162]; hence, the goal is to use LAI and pasture heights as proxies in estimating pasture biomass.

Vegetation indices (VI) are the most adopted retrieval scheme with empirical approaches (Table 4) to estimate the pasture height or biophysical parameters (LAI, fCOVER, ANPP, and fPAR) (Table 4) and relate them with pasture biomass, where the normalized difference vegetation index (NDVI) [45,69,133,166,192] accounts for 83% of this method. Gillan et al. [193] correlated the canopy height (R^2 = 78%) with the ground biomass to infer pasture biomass utilisation at the field scale. Next to NDVI are the enhanced vegetation index (EVI) and soil-adjusted vegetation index (EVI), used with other indices to provide complementary information about their sensitivity to sparse and dense vegetation [74,144,150,181,183]. Index-based retrievals significantly rely on the visible and NIR bands and SWIR for those that require soil water content and dry biomass estimation [149]. A mathematical transformation function (e.g., power and logarithm) is used to normalise data (i.e., expand or compress the index value) to minimise the saturation effects of vegetation indices [64,194].

Table 2. The descriptive characteristics of the satellite instruments used in the review. (*) European Remote Sensing Satellite-1 (ERS-1).

Satellite Instrument	Version	Altitude (km)	Launch Year	Revisit (Day)	Spatial Resolution (m)	Spectral Bands	Red Edge Inclusion	Main Focus	References
MODIS		705	1999/2002	1	250/5000/1000	36(2, 5, 29)	Nil	Regional and global daily application. (MOD 17 model)	[6,71,90,123,124,126,155,156]
Landsat	5 to 8	705	1972	16	15/30/100	11	Nil	Regional and global seasonal coverage.	[78,144,152,154,157–163]
Sentinel-2		786	2015	5–10	10/20/60	13–22	Yes	Flexible resolution (revisit spatial) and red-edge inclusion.	[3,32,50,76,148,164]
SPOT	2 to 7	694	1990–2014	1 to 3	2/8	5	Nil	Vegetation instrument and stereo capability.	[31,149,150,152,165]
AVHRR	1	833	1998–2018	1	1100	5	Nil	Daily global application archive.	[91,166,167]
Sentinel-1		693	2014	6 to 12	Depend on acquisition mode.	3 (0.12–0.50 nm)		Provide global free C-band SAR data. Unique acquisition mode.	[132,168,169]
RapidEye	1 and 2	630	1998–2008	1	6.5	5	Yes	Very high daily global imagery.	[140]
QuickBird		482	2001	1–3.5	0.61/2.4	4	Nil	Very high daily global imagery.	[78]
Worldview	1 to 4	617	2007–2016	<1	0.31/30	29	Yes	More bands for global distinctive imaging.	[170,171]
IKONOS		681	1999	1–3, 14	1/4	4		Very high imaging and stereo capability.	[157,172]
Hyperion		705	2000	16	30	hyperspectral		Narrow bands	[173,174]
ERS-1 *		782	1991		10/30			C-band SAR data and polarization.	[153,175]
Formosat2		888	2004	1	2/8	5	Nil		[176]
PlaneScope		461		1	3	5	Yes	Daily fine global imaging.	[173,177,178]
HySpiri			2018	5	60	hyperspectral		Narrow bands for characterization.	[177,179]
ALOS	1 and 2	628	2006–2014	14, 46	2.5/10	L-band SAR data and 4 optical bands.	Nil	Optical and SAR imaging possibilities.	[7,180]
Venus		720	2017/2005	2	3/5.3	12	Yes	High spatial and spectral application.	[177]

Table 3. Characteristics of major UAS used in the review. The generic name is the instrument's name, while the traditional name is the company's brand name.

Generic Name	Traditional Name	Sensor	Spatial Resolution	Focus	Reference
UAS	Phantom	Multispectral	<1 m	Pasture biomass	[58]
UAS	UAS LiDAR	LiDAR sensor	40 m	Biomass estimation and species classification	[181]
UAS	Phantom and Sequoia	Multispectral	1.5 cm and 3.7 cm	Classifying fractional cover	[116]
UAS	Hexa Copter System	Multispectral	10 cm	Pasture biomass productivity	[182]
UAS + PlanetScope (fused)	MicaSense	Multispectral	30 cm	Aboveground net production	[114]
UAS	Micro MCA	Multispectral	30 m	Pasture quality	[183]
UAS	AisaFENIX	Hyperspectral (VIs-SWIR	1 m	Pasture nutrient	[142]
UAS	HySpex	Hyperspectral	Depend on altitude	Pasture species (classification)	[131]
Airborne laser scanning	Riegl LMS-Q680 sensor	LiDAR; reflectance, echo width NDSM	Depend on altitude	Pasture mapping	[184]
UAS	Hymap	Hyperspectral	5 m	Pasture species (classification)	[52]
Aircraft mounted + calibrate Landsat 5 (TMS)	Very-large-scale aerial (VLSA)	Multispectral of Landsat	1 mm (VLSA), Landsat 30 m	Pasture cover from Landsat calibration	[143]

A physical-based approach using the radiative transfer model (RTM) PROSAIL has been used to retrieve LAI as a vegetation canopy when combined with multispectral satellites [32,135,164,187] and often parametrized and optimised with ML algorithms [45,135,164]. Some studies [32,135] have used proximal hyperspectral data resampled to a satellite multispectral dataset (i.e., Sentinel-2) to constrain the assumption of the homogeneous canopy of the RTM and enhance the accuracy of the model. For example, [32] established a correlation coefficient of 50% between modelled (PROSAIL + resampled data) and in situ biomass. In most cases, LAI correlated better with referenced biomass data than NDVI or other indices [32,188,191]. Furthermore, both the perpendicular vegetation index (PVI) and SAVI derived from Landsat have been found to correlate with the referenced LAI (R = 50%) more than NDVI and other indices [66], confirming the site specificity of LAI-based modelling. Measured LAI is converted to biomass through a linear relationship and compared with the satellite spectral index [32,135].

Other physical-based approaches like the light use efficiency (LUE) (the amount of absorbed photosynthetically active radiation (APAR) that is converted into biomass and expressed as the net primary production (NPP)) model has been used to estimate available pasture biomass (Equation (1) shows the linear association between NPP and LUE).

$$NPP = APAR \times LUE \tag{1}$$

where NPP is the available biomass, expressed as the net primary production (NPP), and APAR is the absorbed photosynthetically active radiation that plants can utilise to produce biomass. MODIS-ANPP products are converted to biomass using biomass-to-carbon conversion [8,90,167]. Liu et al. [35] fused UAS and PlanetScope, while [190] used MODIS to model ANPP as a function of APAR derived from NDVI and light use efficiency (LUE). Similarly, the LUE model has been used to estimate other variables like the green canopy cover, vegetation density, fractional vegetation cover, and fAPAR [8].

Table 5 shows how ML models were integrated with remote sensing for retrievals. Random forest (RF) is the most widely applied ML algorithm due to its capability for regression and classification problems. Generally, ML is used to parametrize index-based retrievals [45,58,74,132,192] more than to retrieve spectral features [3,7]. The ML-based modelling of biomass is more accurate than NDVI [3,74]. Chen et al. [3] established a non-linear relationship between NDVI and in situ biomass. Raab et al. [132] used RF/Support vector machine (SVM)/Multi linear regression (MLR) to parametrize 77 vegetation indices derived from Senitnel-2 to estimate total standing dry matter (TSDM) at an accuracy of R^2 = 45%.

In cloudy situations, authors have used three-dimensional photogrammetric point cloud modelling to assess grassland heights (i.e., between 1–20 cm) with the visible camera from UAS [116,184,185,193]. Gillan et al. [193] found a correlation of R^2 = 78% between aerial imagery and in situ estimates and an average utilisation of 20% from imagery against the 18% of ground-based imagery at a scale of 150 ha. Furthermore, LIDAR has also been used to quantify biomass from different plant species using a 3-D approach at a field level (6.7 ha) with 77% accuracy [181].

Studies have used SAR imagery to complement optical applications using the backscatter signal of microwaves to estimate pasture biomass [7,45,132,153,195] and height [7]. The accuracy of models increases when SAR data are combined with optical imagery compared to a single application. For example, the combination of Sentinel-2, Sentinel-1, and Landsat improved the estimation of biomass by 30% compared to each of the sensors alone [45], and RMSE was significantly lowered when [195] fused Worldview-3 and Sentinel-1. Similarly, the L-band of ALOS (PAR-SAR-2), which is capable of penetrating the canopy structure, was combined with the C-band of Sentinel-1 and 13 spectral bands of Sentinel-2 to map and discriminate pasture heights (short, medium, and tall) from soil inundated with the vegetation canopy using RF [7]. The model's overall accuracy improved (R^2 = 86%) by integrating the three sensors rather than individual contributions.

Furthermore, the wavelet principal component analysis (WPCA) used for SAR and optical image data extraction (based on relevant features) was used to improve the fusion between ERS and Worldview, leading to the higher accuracy of the model [195]. They [195] reported a strong correlation (R^2 = 79%) between the backscatter coefficient of Sentinel-1 and ground biomass from rangeland rehabilitated from mining activities. Similarly, [175] established a strong correlation (59–84%) between ERS backscatter coefficients and targeted wet grassland biomass by applying a linear inversion algorithm to the image data. In contrast, [132] found no significant contribution of Sentinel-1 data when combined with Sentinel-2 in estimating biomass and pasture height in Germany.

3.4.2. Botanical Composition

Some studies have pursued the key objective of finding a suitable instrument to discriminate vegetation canopy. Multi and hyper-spectral sensors $\leq$ 30 m (Tables 5 and 6) are the most deployed to discriminate vegetation canopies with either image-based [33,52,199,200] or object-based image analysis (OBIA) [62,163,169,172,184]. Classifiers derived from hyperspectral sensors are more accurate than multispectral instruments [177,200], while multisource instruments are more accurate than single sensors [113,169,177]. Sibanda et al. [177] established a higher spectral accuracy of 92% from HySpiri than from Landsat 8 (75%), Sentinel 2 (82%), and Venus (83%). Likewise, the study from [113] concludes that IKONOS, QuickBird, and Worldview sensors with finer spatiotemporal resolutions are more sensitive to discriminating grassland from shrubs and trees than Landsat imagery. Studies that used ML algorithms as classifiers (mainly MLC, RF, SVM, and k-Nearest Neighbour (KNN) algorithms) [62,172,199,200] improved their classification accuracy more than traditional methods. For example, the accuracy reached 98% and the Kappa coefficient $\geq$ 90% when ancillary data were added using SVM and RF as classifiers [62]. OBIA enables the mapping of vegetation/species classes and integrations of geometric, textural, and spatial data (i.e., ancillary data) in addition to the primary spectral information to improve accuracy [62,200]. Hence, ML with OBIA can capture the environmental and management variables more accurately than pixel-based algorithms.

Table 4. Summary of the main vegetation indices and associated regression algorithms commonly used in the studies.

Vegetation Indices	Model	Studies Focus	Sensor	Reference
Ratio vegetation index (RVI), enhanced vegetation index (EVI), NDVI	Logarithmic regression	Aboveground biomass	MODIS	[64,189,194,196]
EVI, LAI,	Linear regression model	Aboveground biomass	Worldview, Sentinel-1, Sentinel-2, Landsat	[45,196]
Vegetation indices	Sparse partial least-square regression	Aboveground biomass	Sentinel-2, HySpiri,	[179,197]
		Pasture quality	UAS, AVHRR	[120,142] [91]
NDVI	Power regression	Pasture biomass, forage dry biomass	MODIS,	[91]
LAI derived from satellite	Radiative transfer model	Pasture biomass prediction at the paddock level	Sentinel-2	[32]
NDVI derived from fused satellite sensors	Linear regression model	Aboveground net primary production (i.e., carbon stock) (ANPP) estimated from Absorbed photosynthetically active radiation (APAR) at paddock level	Fusion of Landsat/MODIS	[34]
NDVI derived from fused satellite sensors + UAS	Linear regression + Light use efficiency model	Aboveground net primary production (ANPP) estimated from Absorbed photosynthetically active radiation (APAR)	Fusion of UAS/PlanetScope	[114]
To compare NDVI and FVC derived from UVA (multispectral image)	Exponential function, linear function, logarithmic function, polynomial function and power function	Estimate carbon yield canopy cover for individual plant and across	Multispectral camera (i.e., SpecTerra)	[130]
NDVI + cellulose absorption index derived from satellites	Linear unmixing approach and multiple linear regression	FVC, non-photosynthetic vegetation cover and bare soil	Hyperion and MODIS	[91,141]

More studies have used supervised than non-supervised classification to use novel sampling techniques to build spectral signatures from field areas of interest. Studies have used botanal sampling protocols [139], dominant pasture species [138,161], the percentage of pasture species [33], and the height of pasture species [7,133] to build spectral features. The authors used phenological stages and early growing seasons to improve accuracy using single imagery [49,86,131,201,202]. Wakulińska and Marcinkowska [133] reported a better classification accuracy from a multi-temporal study than a single-date one. Mapping species in the early season reduces canopy complexity and provides insight into their phenology.

The available studies on the combination of optical and radar sensors to discriminate pastures show that the spectral features derived from Sentinel-2 outperformed the backscatter and dual-polarised features of Sentinel-1 [139] when subjected to similar ML models (SVM and RF). However, merging Sentinel-2 and Sentinel-1 produced a higher accuracy (i.e., RF = 93% and SVM = 89%). Like optical sensors, Sentinel-1 data have been used to discriminate between C3, C4, and mixed C3/C4 pastures, using RF to achieve 68% accuracy [138]. The accuracy level increased to 73% on those including textural features (i.e., leaf area, plant height, size, and orientation) derived from Grey Level Co-occurrence Metrics analysis (GLCM). A study used UAS-LiDAR with a 3 cm accuracy level and a maximum 100 m measurement to detect shrub encroachment and classify 2000 habitat types with 75% accuracy, using RF as a classifier [181].

Table 5. The summary of the major machine learning and other retrieval methods used to estimate pasture biomass in the studies.

Methods/Biophysical/ Spectral Parameters	Machine Learning/Model	Approach	Sensor	Ground Approach	Achievement	Reference
LAI derived from satellite	Radiative transfer model + artificial neural network as retrieval	Pasture biomass	Sentinel-2			[135]
NDVI derived from UAS	Statistical (GAM) + Machine Learning (RF)	Pasture biomass prediction at the paddock level	Multispectral camera	Ground calibration with RPM	27% (GAM) and 22% (RF)	[58]
NDVI and spectral variables derived from satellite imagery	Artificial neural network	Pasture biomass prediction at the paddock level	Sentinel-2	Calibration with C-Dax and RPM	51% (ANN) and 39% (NDVI)	[3]
LAI + soil leaf canopy (SLC) derived from satellite	RF + Radiative transfer model (RTM)	LAI and aboveground biomass (AGB)	Sentinel-2	Field sampling	RMSE of 0.4.	[164]
VIs (NDVI, EVI and Land surface water index) derived from satellite	SVM, RF and Multiple linear regression (MLR)	Estimate LAI and aboveground biomass (AGB)	Sentinel-2, Sentinel-1 Landsat	Field sampling (destructive)	30% improvement by combining sensors	[45]
Surface reflectance data (Landsat 8 + MODIS) compared to NDVI, EVI +SAVI	Gaussian Process Regression (GPR)	Estimation of aboveground biomass	Landsat 8 and MODIS	Field sampling (destructive)	GPR outperformed the three VIs R^2 = 0.64 and RMSE = 48.13 g/m^2	[198]
Spectral reflectance	ANN	Quantifying aboveground	Landsat 8	Field sampling (destructive)		[174]
Fractional of Absorbed Photosynthesis Active Radiation (FAPAR) derived from RS	Decision Tree (Machine Learning)	Estimation of herbaceous yield in a (savanna ecosystem)		Traditional FAPAR + meteorological data	ML + FAPAR + climate data performed better than FAPAR model only and/or climate variables.	[99]
LAI + NDVI + Fractional vegetation cover (FVC) derived from satellite	K-NN	Mapping grazing and mowing	SPOT	Field measurement (spectrometer)	82%	[188]

3.4.3. Pasture Management Traits

The main goal is to assess pasture quality using remote sensing as proxies to quantify its management traits [38,46,120,132,140,142,158,170,183,205–207]. Nitrogen availability [140,170,202], soil water condition [67,182,207], irrigation [168], mowing [188,208], livestock distribution [188], soil nutrients [77,142], and fertilizer treatment [207] are the major management traits that have been examined by authors and expressed as pasture quality indicators. Pasture quality has been linked with the aggregation of livestock (animal units) to areas with a rich concentration of nitrogen as a proxy for the abundance of vegetation greenness in mapping the spatial distribution of grazing animals [140,208]. Some studies have used vegetation indices by selecting bands (red, red-edge, NIR, SWIR) of interest with linear regression models to relate them with management indicators [140,170,176,202,208]. Agricultural inputs, such as the irrigation date and LAI, were retrieved from FORMOSAT-2 using spectral indices and integrated into crop models to support water management for grazed pastures in France [176].

Table 6. Summary of the main classification algorithms for pasture composition used in the studies.

Classifier	Methods	Sensor	Accuracy	Reference
SVM + PCA	Pixel-based	Sentinel-2	80% (overall)	[133]
RF	Pixel-based	Sentinel-2, Sentinel-1, ALOS	86% (overall)	[7]
SVM + RF	Object-image based	Landsat		
Kernel + SVM			Non-linear performed better (0.55 $\leq$ R2CV $\leq$ 0.78; 6.68% $\leq$ nRMSECV $\leq$ 26.47%)	[142]
Decision tree	Object-based classification	IKONOS	83%	[172]
SVM				
Decision tree		SPOT		
SVM	linear regres-sion/classification	Landsat		[136]
K-NN		SPOT	Kappa index= 0.82	
Maximum Likelihood Classifier (MLC)	Object-image based	Landsat, SPOT	Landsat = 60.1%, SPOT = 65.5%,	[31]
Multivariate	Hierarchical clustering	Landsat		[203]
RF	Pixel-based classification	Sentinel-1A, Sentinel-2	76%, 62%, 75%	[138]
RF, SVM, KNN	Pixel-based classification	Sentinel-1, Sentinel-2	KNN 0.89, RF 0.96, SVM 0.96	[139]
Multivariate	Where several treatments are needed			[204]
Fuzzy/KNN	Pixel-based	HyMap	98% and 64%	[52]

Other biophysical variables like LAI and fCOVER derived from SPOT imagery have been used with the KNN algorithm to map grazing landscapes to support mowing management [188]. LAI shows a higher correlation of 82% with the sampled data compared to fCOVER. Higher-resolution sensors and/or a combination of multiple sensors have improved model accuracy, especially in a complex field for discriminating grasslands treated with fertilizer (i.e., nutrients) than using one sensor. Sibanda et al. [207] reported an accuracy of 81% for Sentinel-2 and 76% for Landsat (OLI), which were resampled from hyperspectral data in discriminating grasslands treated with fertilizer using sparse partial-least-square regression (SPLSR). The hyperspectral data on its own yielded 92% accuracy. Similarly, HyspIRI data are more accurate (R^2 = 69%) than Sentinel-2 (R^2 = 58%) using wave bands and VIs with SPLSR in predicting burning, mowing, and fertilizer application [179]. However, [140] reported that the accuracy of Sentinel-2 (R^2 = 92%) is higher than RapidEye (R^2 = 53%) in predicting nitrogen concentration levels from simple ratio (SR) and NDVI with RF, due to the three red-edge bands present in Sentinel-2 compared to one red-edge band in RapdEye.

ML models improve the discrimination of grasslands based on management indicators rather than linear regression. For example, [142] reported that RF achieved the best accuracy (R^2 = 78%) in predicting 77% of the macro and micronutrients derived from hyperspectral UAS (spatial resolution ~3.5–11 nm); SVM achieved 86% accuracy for predicting 22% of the nutrients compared to the squares (PLSR) and kernel (PLSR) algorithms. Ancillary data like GPS provide information about livestock distribution and have been found to improve mode accuracy [140,170,208].

3.4.4. Pasture Degradation

The focus is to correlate key anthropogenic activities (i.e., grazing management) that predispose grasslands to decline with remote sensing products as proxies by relating them to biophysical variables (i.e., fPAR, AGB, fCOVER, ANPP). A significant number of studies have used Landsat and MODIS land surface reflectance products rather than finer satellite imagery to express the productivity of grasslands (fPAR) [191,209] (fCOVER) [20,96,137,167,189,190], (AGB, ANPP) [105,109,129,130,141,144,174,186,210,211], and ecosystems beyond the scope of biomass production. NDVI is the most used proxy for estimating biophysical variables. For example, stocking rate data were compared with yearly AVHRR-NDVI and rainfall data to account for overgrazing on rangelands [212]. Soil-based indices are used after NDVI to understand non-vegetation in mapping landscapes [83,144,213]. Haggen et al. [144] used the soil-adjusted total vegetation index (SATVI) from red and SWIR bands to map fCOVER, while [213] estimated the pasture productivity decline from grazing intensity and fire regime in a semi-arid environment using the derived soil tillage index (STI) from MODIS. The study of [213] showed that SWIR calculated from STI (B6 and B7) was more accurate (R^2 = 67%) in mapping drier vegetation compared to NDVI and other indices. LAI was found to be more accurate in estimating fPAR than NDVI [191]. Pasture degradation indicators (grazing intensity/pressure) are often correlated with environmental variables (soil and survey data, meteorological, GPS) to understand the drivers, and are also used with (VIs) as predictor variables [2,20,71,96,105,129,130,141]. Studies have adopted mapping the land cover and land use (LULC) [83,121,199] to show the spatial and temporal variability of an area of interest.

4. Adoption of the Remote Sensing Information by End Users

Table 7 illustrates an overview of the current remote sensing application for pasture monitoring and end users' level of adoption from this review. Studies have shown that farmers, governments, scientists, and spatial consultants are the main stakeholders in the workflow of remote sensing technology (Table 7). For example, the Queensland Government Australia developed an online "FORAGE" (http://www.longpaddock.qld.gov.au/forage/; accessed on 7 February 2021) system to support grazing management and provide site-specific information [214,215]. The customised FORAGE system has provided pasture and climate parameters on land condition and stocking management to 1700 users.

Table 7. Summary of current remote sensing information and forms of adoption by end users.

Remote Sensing Data	Main Focus	End user/s	Country of Adoption	Economic Cost	Year	Inference	Reference
Perspective article: (satellite)	Pasture degradation	Government, pastoralist	Australia and China	Nil	2020	Researchers should partner with end users.	[27]
Perspective article (satellite)	Pasture biomass determination.	Farmers	New Zealand	Nil	2020	Value proposition defines how farmers would adopt satellite data.	[216]
UAS (Phantom)	Pasture biomass/herbage utilisation.	Researchers, rangers, farmers	USA	$1500	2019	Cloud-based remote sensing utilisation where spatial resolution counts.	[193]
Perspective article (satellite)	Pasture management focusing on precision agriculture.	Farmers	United Kingdom and Ireland	Nil	2019	Improvement in pasture quality through management (nutrients).	[215]
NDVI derived from MODIS	Pasture quality.	Farmers	Altai Mountain (Russia, Mongolia, China and Kazakhstan).	Free	2019	Integrate farmers' ground-based pasture management with satellite data.	[217]

Table 7. *Cont.*

Remote Sensing Data	Main Focus	End user/s	Country of Adoption	Economic Cost	Year	Inference	Reference
MODIS derived Enhanced vegetation index (EVI).	Grassland classification.	Policymakers and farmers	China	Free	2018	To manage the carrying capacity of sheep.	[194]
Satellite imagery (Landsat)	FORAGE system estimator.	The general public (emphasis on range managers)	Australia	Free	2018	A web-based system prepared by the Queensland state government, Australia.	[214]
Above Net Primary Production from NDVI derived from MODIS. (Satellite data and GIS).	Forage productivity to manage stocking rate and the carrying capacity.	Policy makers and farmers	Argentina	Free	2007	Monthly monitoring tool within the selected farms.	[8]
NDVI derived from Landsat imagery	Increased pasture productivity by eliminating noxious weeds. Pasture conservation.	Farmers and range managers	USA	Free	2006	An online password-protected decision support tool	[218]
Landsat imagery and GIS system.	Land cover classification and pasture management.	Government, range manager.	China	Nil	2004	Expert system toward database inventory.	[219]
ERS satellite data	Estimating pasture biomass	Policymakers and national agency	Bolivia	Nil	2003	Research was initiated to validate and support a national framework.	[175]
Landsat and SPOT imagery and GIS system.	Data to support pasture management framework.	Farmers	Mongolia	Satellite imagery came with a cost.	1999		[220]
Landsat and SPOT imagery and GIS system.	Pasture growth and productivity through fertilizer application.	Researchers, research institution (CSIRO) and Agric company.	Australia	Satellite imagery was provided through a license.	1996	Research was conducted through a vendor.	[87]

Eastwood et al. [216] acknowledged the low adoption of the remote sensing of pasture monitoring despite increased research and development (R&D) in the past decade. They suggested that there is a need for vendors/researchers to properly understand the "value proposition" of the end users and integrate this into the workflow of the remote sensing technology. An earlier representative study reported by [216] provides an empirical analysis of the current approach to pasture monitoring from interview and survey perspectives. The survey involved 500 New Zealand dairy farmers on the methods used to derive pasture measurement. Fifty-two percent used the visual approach, 45% used a technology-based scheme (RPM, C-Dax), and 3% used neither. Further technology analysis suggested that 32% depend on RPM, 11% use C-Dax, 1% use satellite, and 1% use the contractor. Therefore, although decision support tools are essential, the value of the premium that end users (e.g., farmers) place on pasture monitoring is not entirely sure; hence, the value proposition seems ambiguous to persuade non-users to consider the technology [216].

5. Discussion

This review provides a systematic analysis of published studies on the methods of remote sensing and their usefulness to pasture monitoring in major global grassland ecosystems (Figure 1). All regions and continents of the world are covered (Figure 2). Still, however, less attention has been received from Southeast Asia, the northern part of Latin America (except Mexico), the Middle East (except Iran and Syria), and Africa, with most of the studies coming from South Africa and Ethiopia.

5.1. Trend in the Remote Sensing of Pasture Management Traits, Species Composition, Pasture Production, and Pasture Degradation

Figure 4 shows a deficient proportion of studies from earlier years. Studies have centred on management, and fewer on production, while coverage on botanical composition and degradation was not in the spotlight. There was an increase with time in all topics, especially with botanical composition [221] and pasture degradation [127]. Studies on species/botanical composition may have gained more prominence recently because higher-resolution satellites and UASs for discriminating vegetation canopy are increasingly available for precision agriculture. Furthermore, issues bordering pasture production and degradation due to anthropogenic and climate activities have become prominent in the scientific literature.

5.2. Assessing the Current Remote Sensing of Pasture Monitoring

Despite the widescale coverage of studies and the current utility of satellite sensors (Figure 5a), a high proportion of this effort focuses on regional, continental, and global scales (Figure 8), with less emphasis on field-based monitoring. The number of studies that have focused on fields within 50 ha is less than 20. Higher-resolution multispectral satellites are not free but are also only constrained to a few bands (mainly visible and NIR), except Worldview and Venus, with 29 and 12 bands, respectively (Table 2). Therefore, the publicly available optical satellites MODIS, Landsat, and the recently launched Sentinel-2 have played a central role following their specifications in monitoring vegetation dynamics. Sentinel-2 arrivals in 2015 were thought to address cloud constraints for optical applications, especially with a 5-day revisit and 10 m resolution fleet. This review shows that apart from the over-emphasis on medium to coarse resolutions (Landsat and MODIS), which limited field-based monitoring, the arrival of Sentinel-2 has not resolved missing data due to cloud contamination, especially in places known for persistent cloud cover (i.e., tropical rainforest, mountain regions, and polar and monsoon areas). Researchers have used different approaches to resolve cloud contamination, such as cloud removing algorithms (e.g., CFmask) to mask cloudy pixels [21,45,67,134,136,222], multi-temporal satellite data [7,34,45,132,140,141], and conducting field campaigns in cloud-free days [164], and the stacking of satellite scenes [21,133]. More specifically, researchers and practitioners have used photogrammetry UAS cameral (visible) equipped with a 3-dimensional point cloud [116,184,193] and LIDAR sensors [181] on demand to capture near-real-time imagery as an alternative to satellite applications.

Additionally, the number of studies that have utilised daily and weekly satellite imagery for analysis is less than 20 (Section 3.4.3), meaning that the current revisit would not support/sustain operational pasture management. Intensively grown pastures are dynamic and require more frequent imagery between 5–7 days to capture sward regrowth depending on environmental conditions. The current satellite fleets with daily revisit are not available for public utility, thus limiting this application for R&D. Leveraging radar capability, the all-weather satellite data (i.e., dual-polarisation, backscatter, with C, L, and X bands), especially the free and open-source Sentinel-1 data (R&D) usage in this review, were relatively low (Figures 6 and 7). In most studies involving pasture production (estimation of biomass and height) and species classification [7,45,139,175,195] except a few [132], the integration of SAR imagery has improved model accuracy more than the performance of either the optical or radar data alone. For example, the fusion of ERS and

Worldview imagery using the WPCA method to extract relevant image features in a suitable rangeland environment (i.e., rangeland rehabilitated from mining activities) significantly improved the model performance (R^2 = 79%) [195]. However, with cloud containment, spectral information due to surface reflectance (especially the red-edge and NIR bands) from optical data is more accurate for assessing pasture biomass and discriminating species than dual-polarised features and the backscatter coefficient of Sentinel-1 [132,139]. Hence, optical hyper or multispectral sensors in fair weather conditions offer more accuracy in distinguishing vegetation species than SAR data because of their spectral responses along multiple bands. At the same time, the microwave is not sensitive to chlorophyll content but to the structure and volume of vegetation. Therefore, we conclude that the accuracy of SAR modelling depends on the knowledge domain applied to suit the biophysical variables and target environment.

Generally, the combination of instruments significantly provides a platform to constrain remote sensing trade-offs in an integrated way to fix specific errors or limitations associated with sensors and the target environment. The saturation of biomass (in sparse vegetation and/or peak growing season) associated with vegetation indices [45,223], soil background and topography influence on SAR sensitivity [45], homogeneous canopy associated with LAI [32,135] or with 3-D point cloud photogrammetric mapping [116,193], and spatial, temporal, and radiometric resolution drawback can be addressed using appropriate modelling involving hyper-temporal, multispectral, visible and SAR to improve the accuracy of the model. The SAR backscatter is not sensitive to soil background when the vegetation canopy is low. At the same time, the visible and NIR bands of optical instruments enable the absorption of more radiation than soil, resulting in a higher reflectance for denser canopy areas and lower reflectance values for bare soil. Proximal hyperspectral data were resampled to Sentinel-2 surface reflectance and combined with RTM PROSAIL to estimate LAI, thereby confounding the homogeneous assumption related to RTM [32]. Furthermore, using 3-D point cloud photogrammetric to estimate pasture height and biomass from vegetation volume can be confounded with trees, shrubs, and other land use types, making this approach prone to error. Hence, multispectral bands (i.e., NIR) are included to map land cover or mask the non-pasture community [43,82,83,181].

5.3. Assessing the Approaches Used in the Remote Sensing of Pasture Monitoring

The retrieval of biophysical variables has been significantly restricted to empirical methods using vegetation indices, with NDVI being the most used index to understand pasture production, species classification, management indicators, and the degradation of pastures. Likewise, the physically based retrieval schemes to assess the following biophysical variables—LAI, fPAR, and fCOVER, ANPP—using LUE and RTM are driven by sites and parameters that restrict their generalisation and repeatability. Consequently, their comparison and relationship with the field (destructive and non-destructive field samplings) data has reached a milestone in addressing the problems associated with VIs and physically based modelling approaches, while at the same time revealing the potential areas where more research efforts are needed.

Using ML approaches with careful integration of appropriate satellite sensors in addition to environmental data, the modelling of pasture biomass from the selection of VIs has achieved better accuracy and a higher level of prediction (i.e., an increase from 1500 kg DM/ha to above 3000 kg DM/ha) before reaching saturation [45,223], with red-edge, NIR, and SWIR bands as the main contributors. In contrast, red and NIR bands' usages (NDVI) have continued to trigger a debate on the effect of the saturation, soil background influence, sensitivity to vegetation types, and heterogeneity of canopy-to-model calibration, which have caused researchers to develop more indices and parametrize with ML [45,58,74,132,192] algorithms. However, NDVI has performed poorly compared to spectrally driven ML retrieval (R^2 = 60% and R^2 = 78%), especially when dealing with total standing dry matter [3,74,132]. Therefore, owing to the emphasis on ML-driven index-based retrieval, which is restricted to a few bands and constrained to sites, more research is needed to retrieve a detailed characterization of vegetation properties based on reflectance values, using spectral features to understand the relationship between pixels. The size of field data used for validations in this review is relatively small (test data reveal $\leq$ 120) compared to what is needed (see ~1000 [3]) for training to capture image patterns and improve model calibration.

Apart from the problem of generalisation associated with LAI, fPAR, fCOVER, and ANPP, the biophysical variables are mostly computed from medium to coarse sensors (Landsat and MODIS), which makes them widely applicable (i.e., daily, weekly, and monthly composite global data) but more challenging to use for field monitoring and management. Retrieving these variables from higher-spatial-resolution (1–5 m) sensors will significantly facilitate the monitoring of $\leq$50 ha fields. Indeed, the current hyperspectral UASs (i.e., HyMap, HySpiri, and AisaFENIX with 3.5–11 nm resolution and ~450 bands) have shown great potential in discriminating species and characterizing macro and micronutrients in mixed heterogeneous pastures, which indicates that the availability of these tools (i.e., upscaling to satellites) will significantly enable pasture management at the field scale. Issues relating to costs and logistics would possibly be resolved through disruptive technology and public partnership. The near-future hyperspectral satellites launched by the German (EnMap) and European Space Agency-(ESA) (FLEX) would help determine the cost and logistics, since pilot studies have shown promising results [133,224–226].

5.4. Adaptive Pasture Management and Factors That Influence the Monitoring of Pastures with Remote Sensing

Anthropogenic variables and prevailing environmental factors significantly condition pastures. Therefore, adaptive management that focuses on goal-oriented outcomes using suitable remote sensing tools is highly recommended to improve the sustainability and resilience of pastures and grazing systems over time. Remote sensing products must be appropriately quantified regarding what they represent on the ground. Adaptive pasture management integrates anthropogenic, environmental, and climate variables and remote sensing to provide insight into intensively grazed pasture dynamics, thus making pastures and land management sustainable. This review shows that a combination of different remote sensing strategies, e.g., aircraft imagery and Landsat [121], Phenocam camera [80], and UAS and satellite [114], can be used to understand the temporal and spatial variability of pastures to seasonal and climate change in establishing a framework for adaptive management. For example, a very high temporal time-lapse camera has been used to study the phenology of pasture species at the paddock scale compared with that from the landscape scale using MODIS and Landsat instruments [80]. Consequently, remote sensing products have been used with anthropogenic variables (i.e., stocking rate, grazing survey data, fire, GPS (livestock distribution)) and environmental/climate data (rainfall, temperature, soil) as predictors to improve model accuracy significantly [3,176,212]. However, only 18 studies considered the adaptive management of pastures with remote sensing in this review (Figure 4b). Therefore, more research is encouraged to demonstrate how adaptive management principles with remote sensing tools can support the sustainability of pasture management.

5.5. Analysing End Users' Perception and Adoption of the Remote Sensing Products and Technology

Studies that have considered remote sensing technology's adoption by end users have been few in number. The published dates (Table 7) of the available studies show more efforts in the earlier years than in the last few years. The small proportion of studies on the adoption of the remote sensing of pasture monitoring show that remote sensing products are not at the level of adoption by end users. This review identifies two setbacks to the adoption of the technology. In theory, satellite launchers expect direct benefits of the products for all stakeholders; in practice, the spatial resolutions of the current satellites benefit regional, national, and global applications, as revealed by this review. Currently, the publicly available Sentinel-2 and Sentinel-1 are being under-utilised (Figure 5a). End users may be unlikely to be persuaded to adopt remote sensing technology not at the farm level, which would support management decisions. We recommend future studies to consider monitoring pasture at the paddock level.

The second barrier is the value proposition that needs to be understood by the researchers. Existing knowledge suggests that end users (i.e., farmers) think more of value proposition over the conventional methods (i.e., RPM, C-Dax, visual monitoring) before adopting the technology [87]. From the perspective of service providers, vendors (researchers, consultants, etc.) view remote sensing as input data with other accompanying spatial skills (geographical information system (GIS), information and communication technology (ICT), etc.) in providing end users (i.e., government, range managers, commercial farm enterprise, herders) with customer service that meets specified objectives. Such objectives include (a) providing information that supports the stocking rate and carrying capacity and (b) providing a monitoring system that can reduce degradation and conserve extensive grasslands [27]. End users (e.g., government) view this approach as a knowledge-based conservation strategy. For instance, [70] pointed out that the principal motivation for enacting conservation policies and creating political awareness in some countries is to reduce pasture degradation [75]. For example, China is re-enacting a legislative framework that will prohibit the institutional over-use of grassland that has degraded the country's green land cover due to rapid industrialisation [22]. Summarily, commercial enterprises, satellite launchers, government agencies (Table 8), and service providers (i.e., Earth observation system (EOS), Cibo Labs, AgroInsider, SPACE™, DataFarming, GeoGraze, pasture.io, etc.) entering satellite markets in established countries (e.g., Australia, New Zealand, USA, European countries, etc.) could be the drivers of digital remote sensing of pasture monitoring, and its adoption by end users. High-tech companies such as Microsoft (Microsoft Planetary Computer), Google (Google Earth Engine), Amazon (Amazon Web Services), and Oracle (Oracle Cloud Infrastructure) with cloud computing services are providing applications to support digital agriculture. Social awareness, knowledge, skill, and well-defined research objectives are essential milestones to bring end users into the workflow.

Table 8. Global agencies providing satellite imagery to enable grasslands monitoring on demand.

Name of Agency	Data Source	Data Archive
United States Geological Survey (USGS)	Landsat, MODIS, Sentinel-2, and others	https://earthexplorer.usgs.gov
Sen2Agri	R&D on Sentinel-2 data	http://due.esrin.esa.int/page_users.php
National Aeronautics and Space Administrative (NASA)	MODIS, VIIRS, SMAP (data on vegetation dynamics)	https://www.earthdata.nasa.gov
European Space Agency (ESA)	Sentinel satellites (Sentinel-2 and Sentinel-1 for vegetation monitoring)	https://scihub.copernicus.eu/dhus
National Oceanic and Atmospheric Administration (NOAA)	AVHRR	https://www.avl.class.noaa.gov
Food and Agriculture Organization (FAO)	Geospatial datasets in agriculture and vegetation	https://data.apps.fao.org/map/catalog/srv/eng/catalog.search#/home
Digital Earth Africa (DEA)	Sentinel-2, Landsat, Sentinel-1 and others	https://www.digitalearthafrica.org/
Digital Earth Australia (DEA)	Sentinel-2, Landsat, Sentinel-1 and others	https://www.dea.ga.gov.au/about/open-data-cube
Sentinel Hub	Cloud API for satellite imagery	https://www.sentinel-hub.com/
Google Earth Engine (GEE)	Cloud API for most satellite imagery archive	https://developers.google.com/earth-engine/datasets
Launch RAP (rangeland analysis platform)	Landsat (rangeland monitor for the USA)	https://rangelands.app/
FORAGE	Landsat (rangeland monitor for Queensland)	https://www.longpaddock.qld.gov.au/forage/
Linear Imaging Self-scanning sensor-3 (LISS-3)	Indian satellites (IRS-1C, IRS-1D and Resourcesat-2) for vegetation monitoring	https://www.isro.gov.in/

Currently, ESA (i.e., Sen2Agri) and other global agencies provide a wide range of services to researchers and practitioners aiming to foster (R&D) to make Copernicus programs accessible to the worldwide community.

6. Conclusions

In summary, this review revealed the following trends and research opportunities.

This review simplified the remote sensing of managed global grasslands into four broad areas: management indicators, pasture production, species/botanical classification, and the degradation of pastures from anthropogenic and environmental variables.

In this review, less attention is received in Southeast Asia, the northern part of Latin America (except Mexico), the Middle East (except Iran and Syria), and Africa (except South Africa and Ethiopia).

Low-resolution multispectral sensors (e.g., MODIS and Landsat) are the most used due to availability and low cost. The higher resolution multispectral satellites are not free but are also constrained to a few bands (mainly visible and NIR), except Worldview and Venus, which have 29 and 12 bands.

SAR imagery, especially Sentinel 1 (publicly available), tended to be under-utilised. In particular, SAR data were not applied for mapping management traits and pasture degradation. The utility and accuracy of SAR modelling depend on the knowledge domain used to suit the biophysical variables and target environment.

The hyperspectral sensors used in this review were mainly applied for pasture composition due to the level of detail required.

Integrating multiple remote sensing tends to fix specific errors or limitations associated with sensors and the target environment. However, only some studies have combined sensors (SAR, multi and hyper-spectral images).

Less than 20 studies considered study areas that were less than 50 ha. The number of studies that used daily (i.e., 8) and weekly (i.e., 5) time-series remote sensing products is few, thus, making operational and automation a drawback.

Many studies that used machine learning approaches parameterized the empirical methods by selecting bands, thereby constraining this process to specific sites and parameters. Only a few studies used the characterization of vegetation properties based on reflectance values using spectral features to understand the relationship between pixels.

The size of field data used in most of the studies for validations is relatively small (test data reveal $\leq$ 120), thereby constraining remote sensing products regarding the robustness to capture image patterns and improve model calibration (for machine learning applications).

A few studies (18 studies) considered the adaptive management of pastures, which involved integrating remote sensing products with management and environmental data. It is recommended that future research efforts consider the integration of management and environmental data with remote sensing products for validation purposes and to make pasture management more sustainable.

This review identified that social awareness, knowledge, skill, and well-defined research objectives are essential milestones to bring end users into the workflow. We provided a list of agencies providing remote sensing services that can make the future of global monitoring of pastures more sustainable.

The remote sensing of pasture monitoring with satellites and UAS to derive biomass, LAI, fPAR, fCOVER, ANPP, and quantify physical quantity like pasture heights, discriminate vegetation canopy, manage pasture quality indicators (i.e., soil nitrogen, irrigation, soil water content, fertilizer application, mowing, etc.) and maintain pasture ecosystem from degradation has evolved. In this review, we provided a synthesis of how remote sensing can combine with modelling tools to facilitate the goal of digital agricultural sustainability.

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Appendix A

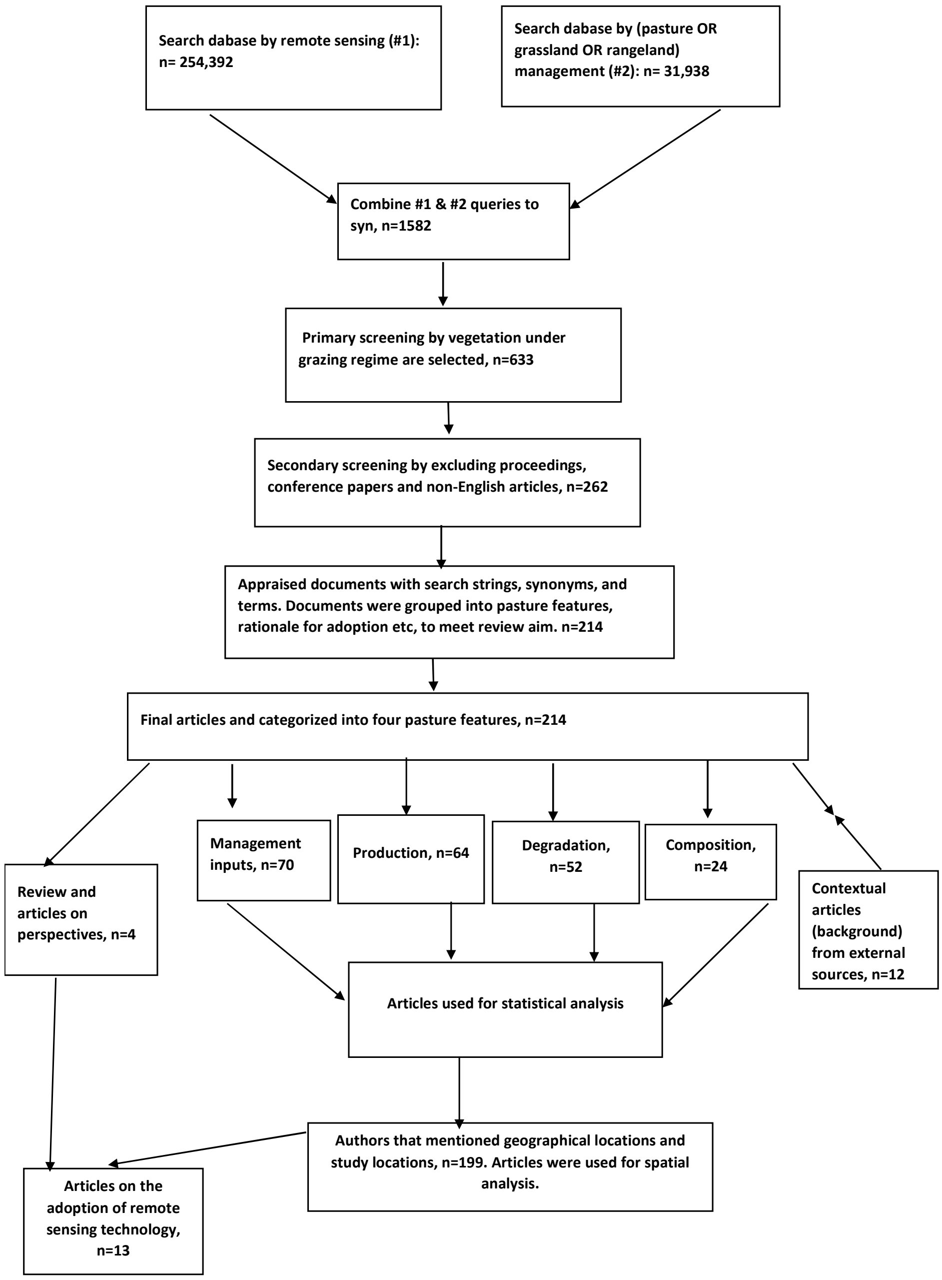

Figure A1. Flowchart describing the systematic literature process.

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